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Detection of human falls using wearable sensors

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Detection of Human Falls using Wearable Sensors

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Abstract

Wearable sensor systems composed of small and light sensing nodes have the potential to revolutionise healthcare. While uptake has increased over time in a variety of application areas, it has been slowed by problems such as lack of infrastructure and the functional capabilities of the systems themselves. An important application of wearable sensors is the detection of falls, particularly for elderly or otherwise vulnerable people. However, existing solutions do not provide the detection accuracy required for the technology to gain the trust of medical professionals. This thesis aims to improve the state of the art in automated human fall detection algorithms through the use of a machine learning based algorithm combined with novel data annotation and feature extraction methods.

Most wearable fall detection algorithms are based on thresholds set by observational analysis for various fall types. However, such algorithms do not generalise well for unseen datasets. This has thus led to many fall detection systems with claims of high performance but with high rates of False Positive and False Negative when evaluated on unseen datasets. A more appropriate approach, as proposed in this thesis, is a machine learning based algorithm for fall detection. The work in this thesis uses a C4.5 Decision Tree algorithm and computes input features based on three fall stages: pre-impact, impact and post-impact. By computing features based on these three fall stages, the fall detection algorithm can learn patterns unique to falls. In total, thirteen features were selected across the three fall stages out of an original set of twenty-eight features.

Further to the identification of fall stages and selection of appropriate features, an annotation technique named micro-annotation is proposed that resolves annotation-related ambiguities in the evaluation of fall detection algorithms.

Further analysis on factors that can impact the performance of a machine learning based algorithm were investigated. The analysis defines a design space which serves as a guideline for a machine learning based fall detection algorithm. The factors investigated include sampling frequency, the number of subjects used for training, and sensor location. The optimal values were found to be 10 Hz, 10 training subjects, and a single sensor mounted on the chest.

Protocols for falls and Activities of Daily Living (ADL) were designed such that the developed algorithms are able to cope under a variety of real world activities and events. A total of 50 subjects were recruited to participate in the data gathering exercise. Four common types of falls in the sagittal and coronal planes were simulated by the volunteers; and falls in the sagittal plane were additionally induced by applying a lateral force to blindfolded volunteers. The algorithm was evaluated based on leave one subject out cross validation in order to determine its ability to generalise to unseen subjects.

The current state of the art in the literature shows fall detectors with an F-measure below 90%. The commercial Tynetec fall detector provided an F-measure of only 50% when evaluated here. Overall, the

fall detection algorithm using the proposed micro-annotation technique and fall stage features provides an F-measure of 93% at 10 Hz, exceeding the performance provided by the current state of the art.

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Acronyms

ADL Activities of Daily Living

DT Decision Tree

EMA Exponential Moving Average

F-M F-Measure

FN False Negative

FNR False Negative Rate

FP False Positive

FPR False Positive Rate

FRAT Fall Risk Assessment Tool

GPS Global Positioning System

HMM Hidden Markov Model

IMU Inertial Measurement Unit

KFD Kernel Fisher Discriminant

K-NN K-Nearest Neighbour

MEMS MicroElectroMechanical Systems

MJHFRAT Modified John Hopkins Fall Risk Assessment Tool

NEAS North East Ambulance Service

NHS National Health Service

PDA Personal Digital Assistant

PIR Pyroelectric Infrared

PSP Progressive Supranuclear Palsy

RMS Root Mean Square

ROC Receiver Operating Characteristic

RMHFRAT Royal Melbourne Hospital Falls Risk Assessment Tool

RMH Royal Melbourne Hospital

SMA Signal Magnitude Area

SMS Short Message Service

SMS Short Message Service

SFRAT Spartanburg Fall Risk Assessment Tool

SVM Support Vector Machine

TN True Negative

TNs True Negatives

TP True Positive

TPR True Positive Rate

VM Vector Magnitude

WEKA Waikato Environment for Knowledge Analysis

WSN Wireless Sensor Network

Chapter 1

Introduction

Small and light wearable sensor systems have the potential to revolutionise healthcare, save lives, and reduce some of the negative impact of ageing.

Mobile wearable sensor systems, and Wireless Sensor Networks (WSNs) in particular, are worn on the body for the purpose of acquiring (and, more recently, autonomously processing) physiological data. Over the years there has been an increase in the use of such systems in a range of application sectors, from sports (e.g. to aid in training) to entertainment (e.g. for motion capture) to healthcare (e.g. for long-term monitoring of patients in their homes). Advances in such technology have been driven in part by the development of MicroElectroMechanical Systems (MEMS) technology for sensors, allowing smaller and lower-power sensors to be produced, and in part by the ubiquitous uptake of devices such as tablets and mobile phones with increasingly high processing capability. Wearable sensors have advantages over ambient sensors in that they are generally smaller and cheaper and are able to track the wearer at any location without requiring additional sensors to be placed in every room.

The need for wearable sensors in the healthcare sector continues to increase for applications such as long-term monitoring of patients in their homes and for shorter-term targeted motion-based studies that previously required manual note taking by the physician. However, the uptake of such technology is relatively slow due to the lack of existing infrastructure within medical facilities and homes, lack of awareness of such technologies within the field, and the reliability of the equipment, particularly with regard to issues such as radio interference, battery life, and the accuracy of detection of events.

One area in which wearable systems can provide a benefit is in fall detection. Falls, particularly among the elderly or infirm people, may result in serious injury or even death if the person becomes incapacitated or fails to seek medical aid. The observation and medical care as a result are estimated to cost the UK National Health Service (NHS) £4.6 million per day. Traditionally, people at risk of falls are provided with pendants containing a button that can be pressed to summon help [72]. However, help may be delayed or prevented entirely due to the person forgetting/refusing to wear remote alarm pendants or deliberately avoiding requesting help. The latter may occur because they feel that their independence is threatened or because they do not want to "be a burden". Furthermore, in case a fall results in a faint, patients will not be able to activate an alarm. An alternative is automatic fall detection via a wearable system. This promotes independent living and safety as it allows the person to live normally in their own home while also ensuring that a carer or medical practitioner is alerted if a fall occurs. As no wearer-accessible activation button is needed, the system can be more easily concealed, reducing the wearer's sense of stigma associated with overt reminders of their vulnerability.

There are two primary ways in which a wearable fall detection system may be used: i) to alert appropriate personnel in the event of a fall and ii) to record fall (or near-fall) frequency in order to enable early detection and diagnosis of medical problems. The former case leads directly to potential saving of lives in the event that the person is incapacitated by the fall. In the latter case, the benefit is longer term in allowing early detection of a potentially dangerous condition, or for the progression of an existing condition to be tracked.

Clearly, to enable the use-cases described, a key component is an accurate fall detection system. While fall detection solutions currently exist, they are susceptible to high numbers of false positives (sending an alert when no fall occurred) and false negatives (not sending an alert when a fall occurred), thus making them unsuitable for general use. Most caregivers do not recommend their use [125]. Towards the goal of providing a high accuracy fall detection system, this thesis presents machine-learning based algorithms for fall detection using wearable sensors (specifically, accelerometers and gyroscopes). The algorithms differentiate between falls and Activities of Daily Living (ADL). Three fall stages are identified and methods for micro-annotation and algorithm evaluation are described.

The remainder of this chapter is organised as follows: Section 1.1 describes the the research questions that guided this work. Section 1.2 describes the approach to research. In Section 1.3 the contributions to knowledge are explained. A list of publications resulting from the work in this thesis are listed in Section 1.4, and Section 1.5 describes the structure of this thesis.

1.1 Research questions

The research questions driving the work in this thesis are as follows:

1. Can machine learning based fall detection algorithms provide performance beyond the current state of the art?
   Fall detection is an established area of research with existing prototype and commercial products claiming high performance for fall detection. These claims do not necessarily match the reality of their in-use performance. This thesis will develop algorithms that provide accuracy beyond the currently available algorithms and will show that machine learning is an important technique for accurate fall detection.

2. Compared to the use of a large set of data features, can a subset of features be selected that does not compromise detection accuracy?
   The set of features that may be of use in detecting falls is potentially very large, with redundancy between features. If the number of features can be reduced to only those required to continue providing a high accuracy then the required hardware resources are reduced, leading to a lower-power and more cost-effective sensing and processing system.

3. What is the design space for a machine learning based fall detection algorithm?
   Design space refers to the set of parameters that must be selected in order to have a well-functioning machine learning based system. If the design space is understood then it can aid in selecting parameters not only for the current work but also for future machine learning algorithms.

1.2 Approach to research

The work in this thesis is experimentally led and aimed at developing accurate and efficient algorithms for fall detection. An in-depth understanding of the sensor signals produced by falls was essential for the algorithm development. To allow this understanding to be developed, data was collected from sensors (accelerometers and gyroscopes) mounted on human subjects (see Chapter 3). As well as providing a better understanding of the falls themselves, this data formed the basis for evaluation of the fall detection algorithms. Falls and ADL were simulated by healthy subjects undergoing protocols designed to provide a range of activity types. While all possible activities and events cannot be simulated in controlled laboratory-based trials, specific requirements for the protocols were identified so that data collected best met the needs of evaluating the developed algorithms. The specification was intended to allow for the inclusion of data that consists of most common activities and events experienced on a daily basis, including:

1. The most common postures an individual will engage in on a daily basis. A given posture will relate to several possible activities, simplifying the problem to an extent. For example, when a subject is sitting and reading a book, the body postures obtained are similar to when an individual is sitting and watching a TV or sitting and talking to someone else.

2. Specific daily activities that the literature notes as being more challenging task to perform. For example, ascending and descending a staircase is considered as a more challenging activity than walking on a level ground [23, 78].

3. Transitions from one posture to another. During normal daily activities individuals will transition from one posture to another, for example from standing to sitting. Transitions must be included as they have the potential to trigger false alarms due to their acceleration signals appearing similar in some respects to fall data (moving from standing to sitting, for example, involves movement of the body downwards).

4. Loss of balance. This represents a near-fall that is recovered from before it actually becomes a fall. This can be of interest to medical practitioners as an early indicator of susceptibility to falls.

5. The common types of fall. Specifically, four types of falls in the sagittal and coronal planes (forward, backward and leftward and rightward falls) were included in the protocols designed.

Four fall detection algorithms were developed and evaluated (see Chapters 4 and 5) based on the data collected. Additionally, the data gathering and annotation process were investigated, leading to the use of several data pre-processing steps along with a new proposed annotation method (micro-annotation).

1.3 Contributions to knowledge

In answering the research questions listed in Section 1.1, the following contributions to knowledge were made:

1. The evaluation of three algorithms for fall detection, demonstrating that when using traditional annotation methods and point-in-time input features (specifically Vector Magnitude here) they do not provide a sufficiently high accuracy. The baseline accuracy considered here is an F-measure of at least 90%.

2. A set of features that provide high fall detection accuracy were identified. By implementing only this feature set the computation required for fall detection is reduced compared to the use of all features in a feature vector, whilst maintaining the accuracy of the algorithm. Embedded microprocessors used in wearable devices have hardware constraints, such as low processing power and low power requirements. Hence, it is essential that hardware resources are efficiently utilised.

3. A fall detection algorithm is proposed and developed based on a new annotation technique (named micro-annotation) and analysis of three distinct stages of fall is performed. This technique provides fall detection accuracy higher than the existing state of the art.

4. A definition of the design space for a micro-annotation based machine learning algorithm and evaluation of factors that influence fall detection. When developing a machine learning algorithm for fall detection, factors such as sampling frequency, training size and sensor location have a large impact on performance. This analysis allows the parameters to be selected to maximise fall detection accuracy.

1.4 Publications

The work in this thesis has led to the following publications:

- **O. Ojetola**, E.I. Gaura, and J. Brusey. **Fall detection with wearable sensors - SAFE (SmArt Fall dEtection)**. In *Proceedings of the 7th International Conference on Intelligent Environments (IE'11)*, pages 318–321, 25–28 July 2011, Nottingham, UK.

- **O. Ojetola**, E.I. Gaura, J. Brusey, and D. Thake. **Machine learning for fall detection**. *Sensors and Interfaces for Cyber-Physical Systems*. N. Medrano, IGI Global Inc. (in print).

1.5 Thesis structure

This chapter presented an introduction to the work in this thesis, research questions, research method and contributions to knowledge.
The rest of this thesis is organised as follows:
Chapter 2 discusses the literature reviewed, relevant to fall detection and the related topics discussed in this thesis. In particular, the algorithms in common use for wearable fall detection are discussed. Chapter 3 describes the methods used for data collection, the set of protocols implemented and the datasets used for algorithm development. The protocols designed were aimed at falls, fall-like events (loss of balance), normal daily activities and activities that require high level of coordination (ascending and descending a staircase). In Chapter 4, three different algorithms for fall detection are investigated and implemented. The algorithms include a machine learning C4.5 algorithms, a Logistic regression based algorithm and a Dot-product algorithm. Chapter 5 describes a micro-annotation based algorithm and investigates the design space for a fall detection algorithm based on supervised machine learning. The development of the algorithm involves feature extraction, feature selection and evaluation. Chapter 6 provides answers to the research questions, presents the conclusions and discusses directions for future work.

Chapter 2

Human Fall Detection: Systems and Approaches

The work in this thesis focuses on the development of fall detection algorithms for use with wearable sensor systems. Thus, this chapter provides a review of the literature in relation to the following topics:

1. An overview of the problem of falls in the UK and the rest of the world.
2. Wearable fall detection systems and approaches to fall detection.
3. The validity of acceleration data gathered from young healthy subjects for development of a fall detection algorithm for the elderly.

The aim of this literature review is to inform the work in this thesis, provide background information and support the developments proposed by the author. Furthermore, this review reveals the gaps in knowledge and practice in the field. The literature review provides support for subsequent chapters in the following ways:

- Chapter 3: The review aided in determining appropriate experimental design and activity protocols.
- Chapter 4: The review identified the current state of the art in fall detection, revealed the weaknesses in existing work, and informed the approach necessary for development of appropriate algorithms.
- Chapter 5: The review informed the development and evaluation of a micro-annotation based algorithm and also aided in defining the design space for a machine learning based fall detection algorithm.

This chapter is structured as follows: Section 2.1 describes falls in the elderly, including a definition of falls and near-falls. Section 2.2 describes common fall detection performance metrics. Ambient based fall detection systems are discussed in Section 2.3. Section 2.4 describes existing commercial wearable fall detection solutions. Section 2.5 investigates falls and near-falls detection in the literature in terms of their data gathering methods, hardware platforms and algorithms. Section 2.6 presents fall detection systems based on mobile phones as a platform. Section 2.7 specifies the design space for a machine learning based fall detection algorithm. Section 2.8 identifies a baseline performance for the current state of the art in fall detection. Finally, Section 2.9 justifies why simulated fall data acquired from the young is valid for fall detection algorithm development.

2.1 Falls in the elderly

Falls are a major cause of health problems for the elderly and can lead to fractures, head injuries, soft tissue injuries, depression and loss of confidence [41, 89, 132]. Patients who fall and are unable to get up or to get help are at risk of dehydration, blood loss (in case of bleeding) or death [69]. Patients hospitalised as a result of falls are prone to further health degeneration [76]. Moreover, falls lead to an increase in morbidity and mortality [109]. Among injuries sustained by the elderly, those from falls pose the most serious health threat [69].

This section gives an overview of issues related to falls in the elderly in the UK and the rest of the world (Section 2.1.1), defines falls (Section 2.1.2), and explains near-falls, which are events which result in loss of balance but not actual falls (Section 2.1.3). Section 2.1.4 discusses the medical approach for fall prevention and fall risk assessment.

2.1.1 Falls statistics (UK and World wide)

Falls are a problem with serious health consequences and affect all countries around the world. This section highlights the seriousness of this problem by describing the impact of falls in the UK and the rest of the world.

UK

According to the National Osteoporosis Society [111], hip fractures cost the UK National Health Service (NHS) over £2.3bn per year. Every minute 6 people over 65 years of age suffer a fall, and every hour an older person dies as a result of hip fracture. The Department of Health noted that early intervention services (such as identifying individuals who are prone to frequent falls and providing necessary monitoring services) could save £5m in reduced cost to the NHS and prevent 400 hip fractures each year if strategic health authorities in England invest £2m in falls [2]. In the UK, each year, this could save 800 lives, 2000 more will be able to walk unaided, 2400 would be able to dress themselves, 3600 would be able to shop unsupervised and 1400 will sleep without pain at night [84].

While most falls are not reported, data collated by the North East Ambulance Service (NEAS) suggests that falls cost the ambulance service £115 per call out [80]. Falls are the main cause of disability and death from injury among people aged over 75 in the UK. Fifty percent of elderly people with hip fractures no longer live independently.

World wide

In the United States, one quarter of the elderly population fall each year which results in over 300,000 broken hips, of which 25% lead to death [64]. In Taiwan, 10.7% of the population are aged over 65 and this number is expected to grow to over 20% by 2025 [68]. In Hong Kong, 111 falls were reported in a retrospective 12 month study which involved a group of 554 community-living elderly people aged over 65 years [33]. Khater and Mousa [53] conducted a one-year study in 3 nursing homes in Cairo, Egypt on the incidence of falls. Overall, 84 residents with a mean age of 71.9 years participated and a total of 163 falls were recorded. Their studies showed that 63% of Egyptian nursing home residents may fall each year. In a survey of randomly selected 4480 elderly people aged over 60 in Thailand, 18.7% were reported to have had one or more falls in the last 6 months [46]. Furthermore, a 12 month study of 2096 elderly people aged over 65 years in Nigeria, found that 23% are likely to fall each year [9]. Of those involved in falls, 45% of women and 30% of men are likely to sustain serious injuries, including hip fracture. As the population of elderly people around the world increases, so will the number of falls and their associated cost.

2.1.2 Definitions of falls

According to Kellogg International Working Group, falls can be defined as unintentional coming to ground or a lower level as a result of a sustained blow, loss of consciousness or health related problems [28]. Moylan and Binder [76] defined falls as unintentional position changes that result in patients coming to rest on the ground, floor or other lower surface. A fall can also be defined as an event in which a body's centre of gravity quickly declines according to Liu and Cheng [68].

The above definitions show a general agreement that falls are unintentional, result in a faller coming to rest on the ground, and may involve causal agents. The following sections further discuss the circumstances of falls and the stages of falls.

Circumstances of falls

As age increases, degeneration of body muscles occurs. This degeneration may result in weakness of bones and skeletal system thus being unable to adequately support the body. Trips and slips are also events that can result in falls. Interventions such as clearing obstacles from paths around the home and administering medical treatments to increase muscle strength can reduce fall incidence. Continuous monitoring will allow fallers to be identified in advance before serious falls occur.

Robinovitch *et al.* [100] found that incorrect shifting of body weight (which causes the centre of gravity of the body to move from the base of support during walking or standing) accounted for around 40% of falls recorded, followed by tripping or stumbling. Slipping was considered to cause the least number of falls. In contrast, Overstall *et al.* [90] considered tripping as the most common cause of falls, but argues that the proportion of falls due to tripping decline with increasing age. Woollacott and Tang [129] suggested that the Activities of Daily Living (ADL) during which falls occur most is walking.

Stages of falls

Paoli *et al.* [92] suggest that falls have the following stages: free-fall , impact, state of motionless and position change. Quagliarella *et al.* [98] investigated falls with loss of consciousness and proposed that falls are characterised by 3 phases; impact, rotation of the trunk region and immobility phase. Kangas *et al.* [48, 50] also identified three stages of fall detection as start-of-fall, impact and posture after fall. In summary, a fall event can be divided into the following 3 stages:

1. Pre-impact: During pre-impact the faller experiences free-fall due to a loss a balance.

2. Impact stage: After the pre-impact stage, a single or multiple impact may be observed. When a subject's body makes contact with the floor or a hard surface, the acceleration of the body is characterised by a brief high acceleration signal.

3. Post-impact: After making contact with the floor, the faller comes to rest. The time it takes for the body to come to rest varies depending on the manner of the fall. At this point, the faller may change their position if they are able.

Identification of these fall stages was necessary in developing the fall detection algorithm presented in this thesis (see Chapter 5).

2.1.3 Near-falls

The high incidence of falls in the elderly can be reduced or prevented through early detection of impairments and functional limitations [61]. Balance disorders which can result in near-falls are a growing health concern due to their association with falls and fall related injuries [114]. A near-fall can be considered as a loss of balance which results from a slip, trip or misstep, followed by successful recovery. Such events do not result in falls [126]. Srygley *et al.* [113] suggested that frequent loss of balance should be associated with increased fall risk and that measuring these events can provide a good understanding of fall risks in individuals who may be prone to frequent falls in the future. Near-falls may be an appropriate fall risk measure and occur more frequently than falls, however such measures rely extensively on self-reporting and often do not get reported at all [126]. According to Nyan *et al.* [83], the most promising prevention strategy for falls is to identify individuals who are at high risk. Therefore, high risk individuals should be continuously monitored in order to reduce fall incidence. An experiment aimed at assessing the feasibility of using a wearable system for gait pattern monitoring was conducted by Ferrari *et al.* [31]. Ferrari *et al.* recruited 5 hospitalised elderly people (1 male, 4 females, mean age 90 years) to assess participant acceptance of a movement pattern monitor, sensor accuracy, and sensor integrity on the skin. Such

Table 2.1: Royal Melbourne Hospital Fall Risk Assessment Tool [71]

movement pattern monitors may be able to identify movement patterns that precede falls, thus allowing falls to be prevented before they occur. Preliminary results showed that all 5 participants agreed that sensors were acceptable, and that skin contact integrity was maintained.

Ideally, detection of falls before they occur is the ultimate solution for fall prevention. Monitoring of near-falls will allow metrics that associate loss of balance to fall risks to be developed and such metrics can be used in fall prediction. While a promising area of research, detecting falls before they occur is outside the scope of this thesis and is considered as future work expanding on that presented here.

2.1.4 Medical approach for fall prevention and fall risk assessment

Primary prevention is considered one of the most cost effective approach in reducing the burden of falls [71]. Thus, the medical domain utilises Fall Risk Assessment Tool (FRAT) to assess and identify patients at fall risk so that preventive measures which can reduce the incidence of falls and its associated injuries can be put in place [107, 39]. FRAT uses multi-factor fall risk assessment such as history of falls, incontinence, impaired vision, chronic pain, muscle weakness and medication to compute scores to determine which patients are at fall risk. Depending on the results from a FRAT, patients are assigned low risk (0 - 4 points), medium risk (5 - 14 points) and high risk (greater than 14 points) [71]. The information derived about each risk level informs on what preventive measures to put in place. Various versions of FRAT exist, tailored to meet specific needs of health institutions. Some examples include Modified John Hopkins Fall Risk Assessment Tool (MJHFRAT) [39], Royal Melbourne Hospital Falls Risk Assessment Tool (RMHFRAT) [71], Spartanburg Fall Risk Assessment Tool (SFRAT) [128] and St. Thomas Risk Assessment Tool in Falling Elderly In-patients (STRATIFY) [127]. An example of FRAT from Royal Melbourne Hospital (RMH) is shown in Table 2.1 [71].

FRATs are not generally considered effective in fall risk assessments [39]. For instance, according to Oliver *et al.* [86], STRATIFY is not an effective tool for identifying high risk individuals. Smith *et al.* [110] conclude from results from an experiment with 387 acute stroke patients, that STRATIFY performs poorly in predicting falls in stroke patients. Similarly, Ma *et al.* [71] suggested from their studies that RMHFRAT is not efficient in predicting falls.

2.2 Fall detection performance metrics

When evaluating the performance of an algorithm, it is essential that appropriate metrics are used so as to understand its performance in a meaningful way. The sets of metrics in common use in the literature include: i) accuracy [68, 74, 36], ii) precision, recall and accuracy [136], iii) accuracy, specificity and sensitivity [117], iv) sensitivity and specificity [94], v) sensitivity [43, 4], and vi) False Positive Rate (FPR) and False Negative Rate (FNR) [26, 133]. In the case of an imbalanced dataset, accuracy does not provide a true picture of the performance of the algorithm being evaluated. For example, given a dataset with 1000 samples of which 20 correspond to falls, an algorithm which always outputs “no fall” will show 98%

accuracy, despite being useless as a fall detector.

In this thesis, fall detection was treated as a classification problem and evaluation was done offline. The number of data sample for falls is very small compared to those for ADL, and therefore metrics other than accuracy are used. The metrics used are precision, recall, and F-measure.

- Precision (or Positive Predictive Value (PPV)): $PR = \frac{TP}{TP+FP}$ indicates the impact of False Positives (FPs) on the performance of an algorithm.
- Recall (or Sensitivity): $RC = \frac{TP}{TP+FN}$ indicates the impact of False Negatives (FNs) on the performance of an algorithm.
- F-measure (or F_1 score): $F_1 = 2.\frac{PR.RC}{PR+RC}$ where PR is precision and RC is recall. F-measure provides a single metric representing the classification performance of an algorithm.

In order to correctly evaluate the performance of the algorithms investigated and developed in this thesis, metrics that indicate the impact of FPs and FNs on performance were used for evaluation. Thus, precision, recall and f-measure were the choice of metrics for algorithm evaluation. Precision indicates the impact of false alarm and recall shows how the number of falls misclassified impact on the performance of an algorithm. The F-measure is a single metric that serves as an indicator for the overall performance of an algorithm in terms of the number of falls correctly classified, false alarms raised and number of falls missed.

2.3 Ambient sensor based fall detection

In the literature, fall detection systems are classified as either ambient or wearable, and this classification is largely influenced by the type of hardware platform around which these systems are built. Ambient solutions use sensors installed in the surroundings of users (for example, pressure sensors, cameras and acoustic sensors) [5, 7, 96]. The following subsections discuss ambient fall detection solutions.

2.3.1 Camera based fall detection

Camera based detection systems make decisions on whether an event is a fall or not by extracting fall patterns from the images captured [54, 87, 115]. A major advantage driving the use of camera based systems is that they are non-intrusive because they do not have to be worn on the body. Nonetheless, they have disadvantages that make them less attractive to users, including:

1. The addition of cameras around a home may be considered an invasion of privacy by the occupants due to the fear that images captured on the cameras can be viewed by a third party. Many falls occur in wash-rooms [49] and patients will generally not accept cameras to be installed in such a place. In a study of the circumstances of falls for elderly people residing in long-term care homes, Robinovitch *et al.* [100] could not install cameras in bedrooms and bathrooms and, as a result, all the falls that occurred in these areas were unaccounted for.
2. Algorithms developed based on camera data are computationally demanding, expensive, and require multiple cameras to be installed around the house. High specification microprocessors are necessary to deliver fall decisions in real-time. Also, in situations in which there are multiple occupants in a room, it becomes difficult to know whom to track [35]. This increases the computation requirements.
3. In order to avoid occlusion, multiple cameras have to installed in places of interest. The use of multiple cameras will increase the cost of the design and implementation significantly.

Despite the limitations described, cameras are still in wide use as a platform for fall detection. Suriani and Hussain [115] used a video camera to model fall events. Their system detects sudden changes which are considered as a deviation from normal activities. These changes are modelled by learning motion history features and the motion geometric distribution across the images in a frame sequence. The authors found that the features implemented (motion history and motion geometric distribution) were able to discriminate between falls (forward, backward and lateral falls) and walk and bend down postures. However, the number of falls classified correctly were not specified. Fu *et al.* [35] also used a camera for fall detection. Their system uses multiple side views of a scene in order to detect accidental events such as falls. Falls are differentiated from ADL by estimating the peak velocity of the subject. Fu *et al.* assumed that falls show more than 3× peak-to-peak vertical velocity than normal walking. They claimed that their system protects patient's privacy by filtering out the detailed visual appearance of patients and processing all images locally.

Furthermore, Liu and Zuo [67] proposed an algorithm that compares the ratio of the width and height of a person while standing and lying, the ratio of the area of a person's figure to the area of the room and the rate of variation of an image during a fall. They concluded that by computing the three features on each image frame, their system will prevent FPs, and thus increase accuracy. However, evaluation results were not presented. Khawandi *et al.* [54] used multiple webcams to perform fall detection. Their algorithm detects faces and measures the speed with which detected faces move toward the ground. Based on a set threshold, it determines if a fall has occurred or not.

Olivieri *et al.* [87] extracted velocity information across video frames and trained a machine learning algorithm to detect falls. Their system was able to detect 99% of falls, but the number of FPs recorded was not reported. Crispim-Junior *et al.* [25] used a video camera in addition to an accelerometer device (strapped to subject's chest) for fall detection. They considered that, by combining the subject's acceleration with visual information, the detection sensitivity and precision could be improved compared to using visual data alone. In their proposed system, the vision component was responsible for detecting a person moving in a room, while the acceleration component detected postures such as standing, sitting, lying and change in postures. The multi-sensor approach (vision and acceleration) resulted in a system with a sensitivity of 93.5% and precision of 63.6%, while the approach based only on vision produced a sensitivity of 77.3% and a precision of 57.7%.

A number of researchers have proposed fall detection using other types of ambient sensors than cameras. Some of these ambient sensors and applications are discussed in the next section.

2.3.2 Other ambient fall detectors

Luo *et al.* [70] developed a fall detection system using 7 Pyroelectric Infrared (PIR) sensors to detect the heat energy emitted by individuals within a room. Each PIR sensor was sampled at 25 Hz and detected the variance of the thermal heat flux within each section of a room. Then, a 2-layer Hidden Markov Model (HMM) classifier was used to model the time varying PIR signal. PIR sensors were used in order to avoid infringing individual's privacy as can happen with cameras. Eighty falls were simulated, but only 87% were classified correctly.

Litvak *et al.* [66] proposed a system based on floor vibration and acoustic sensing for fall detection. Their system acquired sound and vibration data using a microphone and accelerometer, and the algorithm used pattern recognition techniques to differentiate between ADL, humans falls, and an object being dropped/falling. A human-like doll was used in fall simulation and objects such as a bag, plastic box and metal box were used to simulate objects being dropped. The doll was used to simulate 48 forward falls, while the objects were dropped 78 times. An evaluation of the algorithm showed a sensitivity and specificity of 95%. As pointed out by the authors, the fall detection system is not sensitive to low impact falls and was only tested for distances between 2 meters and 5 meters.

The discussions in this section so far have highlighted some of the disadvantages of ambient sensor based systems and that complex algorithms are required for fall detection. On the other hand, wearable sensors are not affected by these disadvantages and are less computationally demanding. Thus, the remainder of this thesis focuses on wearable sensors for fall detection.

2.4 Commercial wearable fall detectors

Wearable fall detectors are generally categorised as *first* generation and *second generation* fall detectors [72]. *First generation* detectors are pendants and wrist bands which allow end-users to summon help by pushing a button in case of an emergency. This type of fall detector do not possess any form of

Figure 2.1: Commercial fall detectors.

intelligence, they rely entirely on the user pushing a button in order to summon help. In circumstances where the user is unable to push the button (for instance, in case of unconsciousness), help will not be available and such a case could result in aggravated consequences.

The *second generation* of fall detectors are automatic or smart fall detectors and are often based on Inertial Measurement Unit (IMU) sensors. A selection of commercial devices in this category are shown in Figure 2.1. They are able to detect falls without requiring any form of input from the user; falls are detected automatically when they occur and calls for help are issued by the device autonomously [97]. Automatic fall detectors also allow alarms to be triggered by the wearer in case of emergencies, similar to *first generation* devices. Commercial wearable intelligent fall monitors include: Vivatec's wrist care [123], Tynetec [119], FALLWATCH (Vigi' Fall) [19, 120, 122], activPAL [91], Philips Lifeline AutoAlert pendant [95], Brickhouse fall detector [3], SafeGuard [103], Task Community Care fall detectors [21] and Tunstall fall detector [118]. Some sensors commonly used in automatic fall detectors are shown in Table 2.2.

2.4.1 Issues with existing wearable fall detectors

Despite numerous commercial and research based solutions, automatic fall detection has several outstanding challenges. A major reason for low acceptance of automatic fall detectors is the high level of FPs and FNs [8, 27].

A FP occurrence is when a fall detection system raises an alarm when no fall occurs. The alarm could be a result of sudden movements such as lying down or sitting in a chair quickly. A FN is when a fall occurs and the fall detection system fails to detect it as a fall. Both FPs and FNs result in lack of trust for the system. For instance, Ward *et al.* [125] reported that health and social care staff are not convinced about the benefits of automatic fall detectors.

In a survey of residents in a sheltered house in Birmingham, Brownsell *et al.* [16] found that some elderly people who had fallen at least once in the previous year refused the use of a fall detector. Their main concern was that the fall detectors may contact the warden unnecessarily in case of FPs. Similarly, Horton [40] conducted a qualitative study to examine whether a fall detector would reduce the fear of falling among community dwelling elderly people who have recurrent falls. While fall detectors gave the users a sense of security, reports showed that over half of the intervention group complained of false

Table 2.2: Wearable sensors for falls and activity monitoring.

Sensor	**Measurement**	**Products**
Accelerometer	Acceleration	Vigi Fall [120, 122], Brickhouse Fall Detector [3]
Gyroscope	Angular velocity	SHIMMER sensors [108], Xsens MVN BIOMECH [130, 99]
Goniometer	Angles (for example: angle of joint movement)	Motion Lab Systems Electro Goniometers [116]
Actometer	Motion	Timex Model 108 Motion Recorder [38]
Pedometer	Step counter (counts number of steps a person takes)	Omron Pedometers [88]
Insole pressure plantar sensor	Pressure distribution across the sole of the foot	Pedar System [81, 63]

alarms and lack of control to determine when to call for help.

2.5 Fall and near-fall detection based on wearable platforms

The previous section highlighted some of the main challenges with existing fall detectors, presenting opportunities for further research. This section investigates existing research methods in the literature. Detection of falls and near-falls detection is discussed under 3 categories: i) experimental data gathering methods and protocols, ii) hardware platforms and sensors, and iii) algorithms and signal processing.

2.5.1 Experimental data gathering methods and protocols

Data gathering is an integral part of the fall detection algorithm development and evaluation process. Data that consist of both falls and ADL is required to develop these algorithms. However, experimenters do not often have access to real fall data. As a result, most research work simulates falls and ADL in a laboratory environment. Before data is gathered, the appropriate number of subjects must be recruited and protocols for the ADL and falls an elderly person would normally encounter on a daily basis must be designed. This section discusses the experimental process used in existing work.

Number of subjects

In order to design a falls and near-falls algorithm that generalises well for a large unseen subject set, it is necessary to train the model and evaluate the algorithm based on data collected from a number of subjects. In the literature, the number of subjects used in training and evaluating varies considerably. Bourke *et al.* [11] recruited 10 healthy young male subjects aged 21–29 years and 10 community dwelling elderly subjects (3 females and 7 males) aged 70–83 years. The young subjects performed falls and ADL while the elderly subjects performed only ADL. Nyan *et al.* [83] recruited 13 male and 8 female volunteers with average ages of 22 and 23 years respectively for their experiments. Weiss *et al.* [126] used 15 subjects—10 young subjects (22–28 years, 4 males) and 5 older subjects (63–77 years, 3 males). Zhang *et al.* [134] employed 12 volunteers (8 males and 4 females), between 10 and 70 years old for their experimentation. Twenty young volunteers (10 males and 10 females, aged 17–32 years) and 5 elderly volunteers (1 male and 4 females, aged 70–83 years) were recruited by Liu and Cheng [68] for their study.

Generally, the number of subjects recruited for fall data gathering exercises varies between 12 and 21 subjects and there is no fixed ratio between genders (males and females) recruited. In majority of the cases, only young healthy subjects (between 17 and 35 years old) were recruited. In only a few cases were elderly people recruited, and they only participated in ADL. The details of the subjects recruited for the work in this thesis are discussed in Section 3.1.1.

Protocols

It is difficult to acquire data based on real falls and not ethically sound to use the elderly and infirm in falls experiments. Therefore, the common practice is to design protocols that mimic real ADL, falls and near-falls and employ healthy volunteers to participate. Much of the literature reviewed in this thesis developed their algorithms based on simulated falls and ADL. For high performance fall detection algorithms to be developed, simulated falls and ADL must closely mimic their real counterparts.

While not all fall types can be simulated, the most common fall events experienced by the elderly are: forward, backward and lateral falls [11, 68, 98, 134, 136]. However, some research has focused on syncope (faint fall) [1, 83, 98].

Bourke *et al.* [11] designed a protocol that consisted of forward falls, backward falls and lateral falls. During data gathering, subjects wore sensor nodes containing 2D gyroscopes on their chest and simulated ADL such as, sitting down and standing up from an armchair, sitting down and standing up from a kitchen chair, sitting down and standing up from a toilet seat, sitting down and standing up from a low stool, getting in and out of a car seat, sitting down on and standing up from a bed, lying down and standing up from a bed and walking. The study by Nyan *et al.* [83] focused on faint falls. Faint falls were simulated by instructing subjects to stand on the floor beside a mattress, relax themselves and fall to the side, back and front. In addition, ADL were simulated by instructing subjects to perform a number of activities such as standing, sitting, walking, lying and ascending and descending on stairs. Subjects wore sensor nodes that consisted of a 3D accelerometer and 2D gyroscope on their chests and thighs during the experiments. Zhang *et al.* [134] designed an experiment based on falls on a soft cushion, falls on a hard surface, stairs and slope (performed by a dummy), fleet movements (lay on the ground quickly and sit down heavily), lie on the ground slowly, walk, jog, run and jump. The subjects recruited wore 3D accelerometer sensors on their waists. Similarly, Liu and Cheng [68] simulated the following falls: forward, backward and lateral falls, slipping while ascending and descending a staircase and falling from a bed. Furthermore, ADL such as ascending and descending stairs, sitting down in and standing up from bed, walking, lying, standing, sitting in and standing from a wheel chair were simulated. A 3D accelerometer worn on the subject's waist was used for data collection.

Only a handful of research works have focused on near-falls detection and the definition of what is considered a near-fall during simulation varies considerably. Weiss *et al.* [126] simulated near-falls by instructing subjects to walk on a treadmill at self-selected paces (slow, normal and fast pace) with obstacles placed in their path out of the subject's view. Subjects wore a 3D accelerometer on their lower back. Events were annotated as near-falls by a volunteer who observed the experiments.

In the literature surveyed, the protocols simulated consisted of both static activities and dynamic activities. The static activities can be summarised as consisting of postures such as standing, lying and sitting. The dynamic activities include walking, ascending and descending a staircase, transitions from one posture to another and falls. In this thesis, protocols were designed to consist of activities people engage with on a daily basis. The set of protocols developed in this thesis are discussed in Section 3.1. The main requirement for protocols is that falls simulated are similar to their real-life counterparts. This is further discussed in Section 2.9.

2.5.2 Hardware platforms and sensors

This section discusses the wearable hardware platforms and sensors used for fall detection. A number of factors influence the choice of hardware, some of which include processing power, sampling rate, power consumption and sensor types (analog or digital). Generally, exact reasons for choosing a particular hardware are not often discussed. As a minimum requirement, it is expected that the hardware platforms used possess the processing power to run the fall detection algorithms deployed.

Bourke *et al.* [11] used a Biomedical Monitoring BM42 data logger, which consists of 2 uni-axial gyroscopes (ADXRS300) for data collection. A DynaPort MiniMod portable was used by Weiss *et al.* [126]. The DynaPort includes a tri-axial accelerometer. Liu and Cheng [68] implemented a system which consists of a tri-axial accelerometer (Kionix Inc., KXPA4-2050, range ±2g), a Bluetooth module (Atrie Inc., BTM-204B), and a microcontroller (Texas Instruments Inc., MSP430F5438). Nyan *et al.* [83] used custom hardware that consisted of a 3D accelerometer and a 2D gyroscope. Paoli *et al.* [92] used a custom platform which consisted of an Atmega 1281 microcontroller, 2.4GHz transceiver radio, 3D accelerometer (Analog devices ADXL345), and infrared sensor. Zhang *et al.* [134] used a tri-axial accelerometer (MM7260Q); further information about their hardware was not provided. Lin *et al.* [65] proposed the use of micro-mercury switch, an optical sensor, and a Bluetooth transceiver embedded in a coat. When falls are detected, a radio notification is sent to a remote Personal Digital Assistant (PDA) which then makes a call to carers. Data from the sensors were combined to determine the posture of the wearer; the micro-mercury switch determines the tilt angle of the wearer, while the optical sensor specifies if the wearer is in a horizontal position or not.

Wearable sensors are often based on off-the-shelf hardware platforms. Generally, these platforms consist of a microcontroller, sensor(s), wireless transceiver, memory and power supply. Wearable fall detectors have resource constraints, such as limited processing power and battery life. However, they are intended to function autonomously, which could be demanding on their limited resources. Thus, the limited hardware resources of wearable systems should be taken into consideration when developing algorithms for such systems. The tree based algorithm proposed in this thesis, for example, is relatively simple computationally and is thus well suited for wearable hardware platforms.

2.5.3 Fall detection algorithms

The algorithms for wearable fall detection systems fall into two categories: those based on machine learning and those based on observational analysis of the data. However, it is known that the latter do not generalise for a wide range of fall instances or unseen subjects. This section reviews fall detection algorithms based on observational analysis, machine learning and a combination of the two. This review informs the work in this thesis and identifies the limitations in the literature. A machine learning based algorithm was implemented and evaluated in Chapters 4 and 5.

Thresholds based on observational analysis

Bourke *et al.* [11] developed an algorithm based on 2D angular velocity sampled at 1 kHz. Features such as Vector Magnitude (VM) for the 2D raw data, integrated 2D angular velocity and differentiated 2D data were computed. Thresholds were set based on observational analysis of the feature outputs. Weiss *et al.* [126] proposed an algorithm for near-falls detection based on 3D acceleration data sampled at 100 Hz. The accelerometer data was first segmented into 5 second non-overlapping window and then low-pass filtered at a cut-off frequency of 1 Hz. For each 5 second data segment, VM, Signal Magnitude Area (SMA), acceleration derivative, maximum acceleration amplitude, maximum acceleration derivative, maximum peak-to-peak acceleration derivative, maximum peak-to-peak acceleration amplitude and the standard deviation were computed. For each feature, the threshold that best discriminated between near-falls and ADL was determined by plotting a range of possible thresholds using a Receiver Operating Characteristic (ROC) curve (a plot for identifying the performance of a binary classifier by plotting the True Positive Rate (TPR) against FPR).

Anania *et al.* [4] implemented a fall detection algorithm based on 3D acceleration data sampled at 100 Hz. A Kalman filter was used to separate the signal component due to gravity from acceleration data and then the trunk inclination angle was computed. Anania *et al.* defined two thresholds; one for the subject's tilt angle and the second for the rate of change of tilt angle. A fall is detected if the subject's tilt angle is greater than the first threshold and when the change in the tilt angle over a short period is greater than the second threshold. Similarly, Perry *et al.* [94] performed fall detection based on 3D acceleration and 3D angular velocity. Thresholds were set based on observational analysis of acceleration, angular velocity and tilt angles. The angular velocity acquired from the gyroscope is a vector quantity, which specifies the rotational speed. The rotational speed is suitable for deriving the tilt angle [85] but not necessarily directly useful for setting thresholds as people do not continuously experience a given rotational speed during falls or ADL.

Wang *et al.* [124] proposed a fall detection algorithm for 3D acceleration data sampled at 200 Hz. Their algorithm was based on simple rules and thresholds were set empirically for 4 different features (VM, magnitude of horizontal acceleration (x and z axes), time from start to end of a fall, and velocity). The time from the start to end of a fall was defined as when the magnitude of horizontal acceleration exceeded 2 g. Events that involve fast movement such as standing up quickly from a sitting posture or bending to pick up an object from the floor can generate acceleration magnitudes greater than 2 g and hence the times recorded as representing falls will not always correspond to actual falls.

Ivo *et al.* [42] computed the derivative of the sum of 3D acceleration fall data sampled at 9 Hz. The threshold was set by observing the amplitude of this derivative. Jantaraprim *et al.* [43] also computed VM for 3D acceleration fall data. A threshold was set to discriminate between falls and ADL by observing the amplitude of the VM. The acceleration data was sampled at 1 kHz and each axis was low-pass filtered (Butterworth filter) with a cut-off frequency of 20 Hz.

Tolkiehn *et al.* [117] noted that, in addition to detecting falls, it is necessary to identify the direction of falls in order to identify parts of the body that have weak joints or have been fractured. Thus, they proposed an algorithm that uses 3D acceleration and pressure data sampled at 10 Hz to detect falls. Features such as VM, tilt angle and change in pressure were extracted. Thresholds were set manually for VM and tilt angle. If the VM and tilt angle values go beyond the set thresholds, the algorithm checks if a change in pressure also occurred.

The papers reviewed here have based their algorithms on thresholds determined using observational analysis of fall data. While the features computed in those papers are relevant for fall detection, the thresholds set manually for a fall or no fall condition will not allow for algorithms that generalise well for a variety of unseen subjects and different fall types to be developed. Hence, it is inefficient to define thresholds based on a few fall instances observed. A more appropriate approach is to develop fall detection algorithms based on machine learning [85].

Thresholds based on machine learning

In the previous section, algorithms based on thresholds set by an observational analysis of fall data were discussed and their limitations identified. This section reviews the literature with regard to machine learning algorithms for fall detection.

Liu and Cheng [68] proposed the use of a Support Vector Machine (SVM) for fall detection. Features were developed using 3D acceleration data sampled at 200 Hz. The features extracted include the VM, the difference between the maximum and minimum acceleration for each axis of acceleration, the vertical acceleration and the tilt angle.

Zhang and Sawchuk [133] proposed a fall detection framework that combines decisions from a fall detection algorithm with context information using a Bayesian network. The context information includes physical activity level, personal health record, blood pressure level, heart rate and location (indoor or outdoor). Zhang and Sawchuk suggested that context information can help reduce FPs. A Bayesian network was constructed to combine the probabilistic dependencies between the fall detection system and contextual information, and it performs inference on the likelihood of a fall in a given context. However, gathering physiological data such as blood pressure level and heart rate requires additional sensors to be worn by subjects and thus will affect the acceptability of such systems.

The algorithms discussed so far have been based on sensors worn on subjects' bodies. However, Lan *et al.* [59] embedded a 3D accelerometer, 3D gyroscope and two pressure sensors in a walking cane. The two pressure sensors were fixed to the handle and the tip of the cane and measure the grip and the downward-push force, respectively. The accelerometer and gyroscope measure the acceleration and angular velocity of the cane. A Decision Tree (DT) and subsequent matching (a technique in data mining for finding exact or closely matching segments of a much longer sequence) were used to discriminate between falls and ADL. Data were sampled at 26 Hz. The main challenge of the system is in differentiating between whether an individual has fallen or the cane was just dropped or left on the floor. Furthermore, authors noted that the system gives FNs in cases where the cane hits an obstacle midway during a fall before coming to rest.

It is the opinion of the author that machine learning algorithms and features as used in the work described here are not sufficient on their own. Features should be computed based on distinct fall stages (as described in Section 2.1.2) in order to provide accurate fall detection. Section 5.3 discusses feature extraction based on fall stages as implemented in the work here.

Combination of observational analysis of thresholds and machine learning approaches

In the previous sections, fall detection algorithms based on thresholds set either by observational analysis or machine learning approach were discussed. Another approach for fall detection algorithms is to combine both methods discussed above. This section discusses algorithms developed in this way.

Gjoreski *et al.* [36] combines posture recognition with thresholds set by observation analysis to detect falls. Their algorithm uses 3D acceleration data sampled at 6 Hz. The extracted features were VM, tilt angle, mean of accelerometer x-axis, Root Mean Square (RMS) of VM, standard deviation of VM and change in VM. Postures (such as such as lying or sitting on the floor) are recognised via a Random Forest machine learning algorithm. A fall is detected by combining the recognised posture with a threshold set for the VM. If a subject's posture is lying or sitting and the VM goes above the threshold, then a fall is detected. The main drawbacks with this algorithm are i) thresholds set manually do not generalise well for unseen subjects, and ii) only 2 postures are considered as corresponding to falls, however fallers may end up in other unrecognised postures such as crouching and kneeling.

Summary of fall detection algorithms

A summary of the types of falls simulated and hardware used for data collection in the literature is presented in Tables 2.3, 2.4, and 2.5. Thresholds set by observational analysis do not require the computation associated with training machine learning algorithms, and do not require the real-time use of a learned model. However, the complex nature of human movement makes such thresholds less effective in detecting falls for different fall types and unseen subjects. Thus, a machine learning approach is a more appropriate approach for generalised fall detection. DTs are proposed as a suitable fall detection algorithm in this thesis. DTs are well suited for embedded level applications, such as those used in wearable systems [17]. For a tree based system, fall thresholds are determined off-line, and these thresholds can be used in real-time applications. An approach for fall detection that resolves all the limitations of the algorithms identified in this section is discussed in Chapter 5.

2.6 Mobile phones: a platform for fall detection

Recently, advancements in mobile technology have resulted in increased use of smartphones as a platform for fall detection. Over the years, the processing power of mobile phones has increased and most phones are now being equipped with accelerometers. The reasoning behind the adoption of smartphones as a fall detection platform is that they are ubiquitous; many people now own smartphones. This section discusses fall detection systems based on mobile phones.

Martin *et al.* [73] proposed the use of a mobile phone for fall detection. The mobile platform uses Global Positioning System (GPS) to track users positions and uses a tree based algorithm to discriminated between falls and ADL. When a fall is detected, the system makes a call or sends a Short Message Service (SMS) message to carers. The system therefore takes advantage of mobile phone technologies (such as GPS and SMS) to manage an automatic fall alert system. However, the use of mobile phones as a platform for fall detection adds an additional layer of complexity as, aside from discriminating between falls and ADL, algorithms must also be able to identify when phones are in normal use or dropped to the floor. Evaluation results were not provided. Similarly, Zhoa *et al.* [136] identified fallers locations by using wireless network infrastructure distributed within a building, with notifications being sent to carers whenever falls are detected. A tree based machine learning algorithm was implemented for fall detection and features such as mean, standard deviation, slope, energy and correlation were used as input. Ten subjects (5 for training and 5 for testing) were recruited for their experimentation and the phones were

Table 2.3: Summary of papers on fall detection.

Authors	**Hardware Platform**	**Sensor Placement**	**Sampling Frequency (Hz)**	**Number of Subjects**	**Ages (years)**	**Algorithms**	**Falls**	**Near-Falls**	**ADL**
Bourke *et al.* [11]	BM42 data logger (2D gyroscope (ADXRS300))	chest	1000	20 (10 young, M), 10 elderly, 3 F and 7 M))	young (21 -29), elder (70-83)	Threshold based (set manually)	forward, backward, lateral	-	Standing, sitting, getting in and out of car, lying getting up from bed and walking.
Nyan *et al.* [83]	custom made, 3D accelerometer and 2D gyroscope	waist and thigh	47	21 (13 M and 8 F)	mean 22.5		syncope	-	standing, sitting, walking, lying, ascending and descending on stairs
Weiss *et al.* [126]	DynaPort MiniMod (3D accelerometer)	lower back	100	10 young (4 M), 5 elderly (3 M)	young (22-28), elderly (63 - 77)		-	trip caused by obstacles	walking on a treadmill
Zhang *et al.* [134]	3D accelerometer (MM7260Q)	waist	512	12 (8 M)	10 - 70	one-class support vector machine	forward falls on hard and soft surfaces	-	lying, walking, jogging, running and jumping
Liu and Cheng [68]	3D accelerometer (KXPA4-2050), Bluetooth (BTM-204B), Microcontroller (MSP430F5438)	waist	200	20 young (10 M), 5 elderly (1 M)	young (17 -32), elderly (70 - 83)	Support vector machine	forward, backward, lateral, lateral, slip and falls from bed	-	walking, lying, sitting, ascending and descending stairs
Klenk *et al.* [55]	Dynaport MiniMod data logger, 3D accelerometer (LIS3LV02DQ)	lower back	100	15 young (7 M), 4 elderly (all F)	young (mean 24.1±1.9) elderly (mean 68.8±4.5)	-	backward	-	unscripted ADL
Abbate *et al.* [1]	Nexus smartphone, 3D accelerometer (BMA150)	waist	50	7 (5 M and 2 F)	20 - 67	threshold (set manually), neural network	forward, backward, faint	-	sitting, walking, running,
Zhao *et al.* [136]	Mobile phone (N95), 3D accelerometer, Wi-Fi module	-	32	10 (- M, - F)	-	decision tree	forward, backward and lateral (left and right)	-	Walking, running and standing
Quagliarella *et al.* [98]	3D accelerometer (2 orthogonal biaxial ADXL210), data logger	-	100	10 young (6 M, 4 F), 10 elderly (5 M, 5 F)	young (mean age 33.6±1.2), elderly (mean age 75.8±3.2)	Threshold based (set manually)	forward fall, slow forward, lateral (left and right), and backward	-	Walking, sitting, lying, bending to pick an object

Table 2.4: Summary of papers on fall detection.

Authors	**Hardware Platform**	**Sensor Placement**	**Sampling Frequency (Hz)**	**Number of Subjects**	**Ages (years)**	**Algorithms**	**Falls**	**Near-Falls**	**ADL**
Ferrari *et al.* [31]	Accelerometer	wrist, leg, chest and ankle		5 hospitalised elderly (1 M, 4 F)	mean 90.2	questionnaires (qualitative)	-	-	Sit-up on a bed
Mi-hee *et al.* [74]	3D accelerometer (ADXL330), SD card, Zigbee (CC2420), Microcontroller (Atmega128)	waist	100	10 young (3 M and 2 F)	24 - 33	Fuzzy c-means classification algorithm	-	-	include standing, sitting, lying, walking and running
Tolkiehn *et al.* [117]	3D accelerometer (ADXL330), Barometric pressure (VTI SCP 1000-D01) sensor	waist	10	12 (8 M and 4 F)	mean 26.25	Threshold based (set manually), VM, standard deviation	forward, backward, lateral	-	sitting, standing, lying, jumping , walking, lean against a wall
Boyle and Karunanithi [15]	2D accelerometer (activPAL)	waist	10	1 (M)	-	threshold based (set manually), ROC	forward , backward, lateral, trip fall	-	Walking, standing, sitting, lean forward
Perry *et al.* [94]	3D accelerometer and gyroscope (SHIMMER sensor)	hip	100	2 (M)		threshold based (set manually)	forward, backward, lateral (left and right)	-	jumping, sitting, standing, walking
Anania *et al.* [4]	3D accelerometer (ADXL330), microcontroller (MSP430F149) , Bluetooth	trunk	100	-	-	threshold based (set manually), Kalman filter	falls while walking, jumping, running and resting	-	Walking, running, jumping,
Kaenampornpan *et al.* [47]	3D accelerometer, mobile phone (Nokia N97)	left chest pocket	-	1 (M)	-	threshold (set manually)	forward, backward, lateral (left and right)	-	walking, jumping, walking up the stairs and standing still
Dai *et al.* [27, 26]	3D accelerometer, mobile phone, magnetic sensor	chest, waist and thigh	-	15 (13 M and 2 F), 1 mannequin	20 - 30	threshold based (set manually), ROC	forward, backward and lateral	-	walking, jogging, standing, sitting
Lan *et al.* [59]	3D accelerometer and gyroscopes, pressure sensors (smartcane), Bluetooth, microcontroller (MicroLEAP)	walking-cane held for support	26	3 (2 M and 1 F)	25 - 35	decision tree, subsequent matching	forward, backward and lateral	-	walking, standing, sitting, lying

Table 2.5: Summary of papers on fall detection.

Authors	**Hardware Platform**	**Sensor Placement**	**Sampling Frequency (Hz)**	**Number of Subjects**	**Ages (years)**	**Algorithms**	**Falls**	**Near-Falls**	**ADL**
Wang *et al.* [124]	3D accelerometer	behind the ear	200	5 (3 M and 2 F)	-	threshold based (set manually)	forward, lateral (left and right)	-	standing, sitting, lying, walking, jumping, jogging, ascending and descending stairs
Martin *et al.* [73]	3D accelerometer, mobile phone	-	-	-	-	decision tree	forward, backward	-	standing, walking, sitting, ascending and descending stairs
Jantaraprim *et al.* [43]	3D accelerometer (ADXL321 (2))	trunk	1000	10 young (7 M and 3 F), 10 elderly (7 M and 3 F)	young (27 ± 4.6) elderly (69.7 ± 4.3) (2.1)	threshold (set manually)	forward, backward, lateral (left and right)	-	sitting, lying, walking, standing, bending down
Zhang *et al.* [134]	3D accelerometer (MMA7260Q), single chip modem (MSM7512BRS), mobile phone microcontroller (PIC18F2455)	-	128	20 young, 12 elderly, 1 mannequin	young (20 - 39) elderly (60 - 80)	SVM,Kernel Fisher Discriminant (KFD), K-Nearest Neighbour (K-NN)	fall on soft and hard surface, falls on stairs	-	walking, jogging, sitting, lying
Zhang and Sawchuk, [133]	Sun SPOT (802.15.4 transceiver, 3D accelerometer (LIS3L02AQ), microcontroller)	wrist	100	4 (- M, - F)	-	SVM, Bayesian network	forward, backward, lateral (left and right)	-	walking, running, lying, standing
Gjoreski *et al.* [36]	3D accelerometer	waist, chest, thigh and ankle	6	11 young (7 M, 4 F)	-	Random Forest, threshold set manually,	tripping, falling slowly and quickly from a chair	-	Lying, sitting on chair, standing, sitting on ground, walking
Vallejo *et al.* [121]	3D accelerometer (ADXL345), microcontroller (MCF51JM128), zigbee module	waist	-	11(9M and 2 F)	19 – 56	Artificial Neural Networks (ANN)	-	-	Unscripted ADL

strapped to subjects waist. No false alarm was recorded and the system had a recall of 75%. The work assumed that phones are permanently strapped to the waist. In reality, phones are never strapped to the waist and are instead held in pockets. Additionally, the owner will hold their phones to make calls and send texts, and sometimes will drop their phones on the floor. Algorithms developed for use on smartphones need to consider how phones are used rather than only considering a simple but unrealistic use-case.

Sposaro and Tyson [112] used an Android-based smartphone for fall detection. Their algorithm was based on a threshold set for the VM of 3D acceleration data from the phone. Pre-determined thresholds were selected depending on whether the phone is in a chest pocket, back pocket or held in the hand. Sposaro and Tyson noted that their algorithm triggers a false alarm whenever the phone is dropped and will require users to deactivate the alarm if such incidence results in a false alarm. Such inconvenience will discourage use of the detector by users. The performance of their algorithm was not reported. Kaenampornpan *et al.* [47] in their study assumed that phones are placed normally at the left chest pocket and thresholds were set for the minimum and maximum acceleration reading of a subject's body during ADL and falls. Their system expects that users simulate falls the first time the phone is in use so that the acceleration threshold could be set to user specification. In addition, if the system detects a fall, the fall will only be registered if the user does not recover from the fall after 30 seconds. Some of the limitations of the include: i) The algorithm will only work with a phone placed in the left chest pocket, ii) subjects are required to determine their own fall threshold by first simulating a fall before the fall detection system will correctly detect falls (elderly people will not be able to simulate a fall before using the phone fall detector and a threshold that generalises for different fall type will require various fall instances in order to select optimum threshold), and iii) a fall recovered from within 30 seconds will not be considered a fall. Even if a faller recovers from a fall with 30 seconds, the fall should still be detected and registered. Registering falls which do not result in fatal consequences can give clues on the likelihood of a severe fall occurring in the future.

Dai *et al.* [26, 27] suggested that fall detectors should be based on existing pervasive devices, hence they used a smartphone as a fall detection platform. Their algorithm was based on thresholds set for both the VM and the acceleration in the vertical direction. The algorithm was tested with the phone placed at the chest pocket, waist and trouser pocket. To enhance the performance of their system, a magnetic sensor was strapped onto the subject's lower leg. The waist was considered as the best location to place a phone for fall detection and the evaluation of the system reported an FNR and FPR of 2.1% and 7.7% respectively. Similar to previously reviewed literature, their algorithm did not consider the normal daily use of the phone. Zhang *et al.* [134] proposed a system that consisted of an external 3D accelerometer interfaced to a mobile phone. Their system used an SVM for pre-processing and KFD and K-NN for the classification of activities into falls or ADL. Their algorithm was based on the theory that a faller will remain motionless immediately after a fall and the state of motionlessness was observed in the VM value. Once this state of no motion was observed, the classifier algorithm (KFD and K-NN) determines if an event was a fall or not. The location on a subject's body where the sensor and phone were placed was not specified in this study. Abbate *et al.* [1] strapped smartphones on their volunteers waist while conducting a survey on the acceptability of a smartphone as platform for fall detection. Ten volunteers (6 male and 4 female, 60–82) participated and 40% noted that they would not like to wear a phone on their waist.

The level of acceptance of mobile phones for fall detection among the elderly is still very low. Smartphones are ready-made platforms for fall detection systems, because they have the processing power, sensors, and communication modules already integrated together. However their use introduces new types of challenges. The challenges associated with the use of smartphones for fall detection are: i) most elderly people do not carry their phones with them while at home, ii) since mobile phones are not meant to be strapped to the body, a more sophisticated algorithm will be needed to track the position and orientation of the phone during normal daily use, including if it drops to the ground. Thus, the use of smartphones as a fall detection platform does require combining acceleration models of normal use of phones with human movement patterns in order for falls to be detected.

The main issue with fall detection is often not the platform itself, but the high rate of FPs and FNs. Human movement is complex and this makes fall detection challenging. Although, smartphones have the sensors, processing power and communication module already integrated, most can not offer the battery life required for continuous monitoring.

2.7 Fall detection algorithm design space

The design space for fall detection algorithm development defines a variety of parameters that can impact on the performance of a fall detection algorithm. No standards for fall detection algorithms exist, and the reasons for selecting a particular parameter are not often stated [105]. This section discusses the design space for fall detection in relation to 4 major parameters: sampling frequency, sensor placement and number, data features extracted, and training set size.

2.7.1 Sampling frequency

When developing algorithms for fall detection on embedded platforms, it is advantageous that data are sampled at low frequencies whilst still maintaining performance. Sampling at low frequencies implies a low processor resource requirement and low power requirements. The sampling frequencies in the literature surveyed varied from 6 Hz to 1 kHz (see Tables 2.3–2.5). The reasons for sampling at specific frequencies are often not specified. Antonsson and Mann [6] asserted that 98% of the power in human gait is contained below 10 Hz. Brusey *et al.* [17] showed that sampling at 10 Hz is sufficient for posture classification. Other fall detection algorithms in the literature also used data sampled at 10 Hz [15, 117]. The impact of sampling rate on detector performance is investigated here in Section 5.5.4.

2.7.2 Sensor placement and number

There are a number of body locations used for sensors in the literature, including: waist [15, 68, 117, 134], thigh [26, 82, 85], hip [94], trunk [43, 4], chest [11, 26, 36], lower back [55, 126], lower leg [31, 36], wrist [30, 133] and behind the ear [124]. For everyday use, multiple sensor nodes cannot be placed on a person. Ideally, to minimise discomfort, only one sensor node should be attached to a patient. For this reason, some investigation has been carried out regarding the best location for sensors to provide optimum algorithm performance. Doughty *et al.* [30] evaluated a Tunstall fall detector strapped to the chest, waist, knee, wrist and arm. They concluded that the chest and waist are the most appropriate locations of the body to place fall detectors. Furthermore, the arm and the wrist were considered unsuitable because they allow a wider range of movement, which can confuse a fall detector. Similarly, Gjoreski *et al.* [36] investigated the placement of sensor nodes on the chest, waist, thigh and ankle. Results showed that placing a fall detector on the chest provided the best performance, followed by the waist. The literature reviewed suggests that the chest is the best location to place a sensor node for fall detection. Thus, the work in this thesis compares the performance of a fall detection algorithm based on sensor node placed on the chest and on the thigh (see Section 5.5.3).

2.7.3 Feature extraction

Identifying optimum number and type of features is an integral part of fall detection algorithm development. As noted by Neagu *et al.* [79], finding the optimal feature subset is as important as selecting an appropriate algorithm.

Some researchers compute features for acceleration only [26, 44, 47], while others do so for the acceleration and tilt angles [1, 20, 62, 112, 134, 4, 36] (as a proxy for posture). Li *et al.* [62] observed the tilt angle of a faller and measured the maximum VM if the subject is in a lying posture. Similarly, the algorithm presented by Chen *et al.* [20] computed the VM of acceleration and if the VM is higher than a set threshold then it computes the tilt angle before and after the suspected fall. Bourke *et al.* [14] showed that the velocity and rate of change of acceleration of a faller is always higher during a fall than in ADL.

The features extracted in the literature include: VM, SMA, velocity, variance, peak-peak acceleration, RMS, moving average, tilt angle and energy. Feature extraction and selection are discussed in Chapter 5.

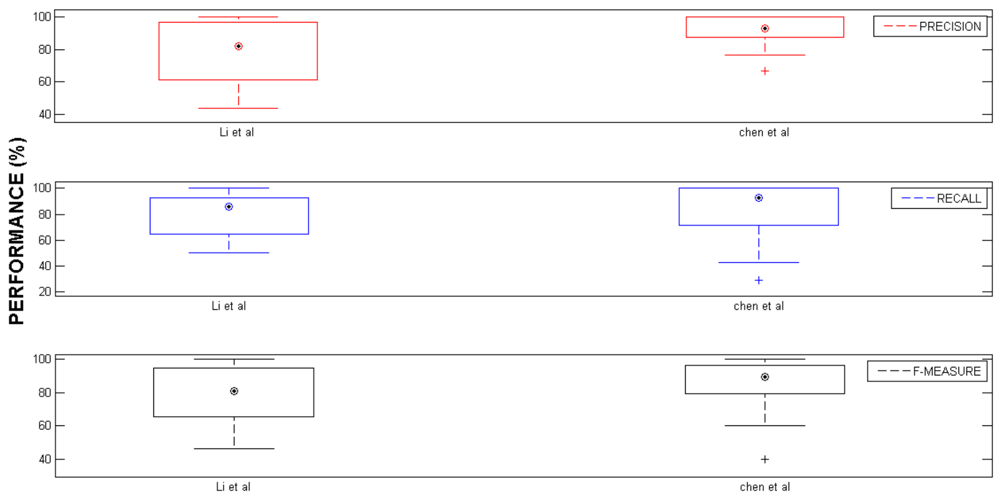

Figure 2.2: Evaluation results for the algorithms presented by Li *et al.* and Chen *et al.*

2.7.4 Training set size

For machine learning based fall detection algorithms, the minimum training dataset size is not often investigated in the literature. It can be assumed that experimenters normally use all the subjects they are able to recruit. Machine learning based algorithms require a minimum number of subjects to simulate falls and ADL in order to provide a good performance. On the other hand, training with more subjects than needed do not often lead to improved performance and sometimes can impact on performance. Thus, it is necessary that the minimum number of subjects required for training are identified during algorithm development. The number of subjects recruited in the literature for falls and ADL simulation was discussed in Section 2.5.1. In this thesis, the minimum number of subjects required for training a micro-annotation based fall detection algorithm was investigated in Section 5.5.5.

2.8 Baseline performance for the state of the art in fall detection

This section aims to identify the baseline performance for the state of the art in fall detection. A baseline is needed to determine the minimum performance required from the algorithms developed in Chapters 4 and 5. In order to determine a baseline performance for the algorithms developed in this thesis, evidence of the fall detection algorithm performance was drawn from the literature, two algorithms in the literature were implemented and evaluated, and a commercial fall detector (the Tynetec fall detector) was evaluated. Bagala *et al.* [8] evaluated 13 algorithms and found them to have an F-measure less than 90%. In addition, in this thesis, the algorithms presented by Li *et al.* [62] and Chen *et al.* [20] were implemented and evaluated and found to have an F-measure of 79% and 83%, respectively. A summary of the evaluation results is shown in Figure 2.2. Furthermore, a commercial fall detector was evaluated and was found to provide performance with an F-measure of 50% (see Section 3.3). These evaluation results show that the current baseline performance is less than 90%.

2.9 Fall data from the elderly

As mentioned previously in Section 2.5.1, most algorithms for fall detection are developed and evaluated based on data from healthy young volunteers [12, 15, 27, 58, 62] because it is not ethically sound for the infirm and elderly be used in such experimentation. Due to this limitation, it is important to understand the differences and similarities in movement patterns between the elderly and young healthy volunteers. An understanding of the differences and similarities in movement between the young and the elderly will allow algorithms that provide high accuracy to be developed.

Coordination is the process by which the movement of the limbs and body parts are organised in time and sequence with respect to functional movement pattern [104]; coordination decreases with increase in age. The elderly often have less control over the speed of their body movement during normal daily activities due to reduced muscle strength [11]. Byrne *et al.* [18] compared lower limb coordination during walking between young and elderly women and found less coordination between the thigh and shank (part of the leg between the knee and ankle) during braking periods in the elderly. Some research groups with access to fall data from the elderly have performed experiments that compared fall data from the elderly with simulated data from the young. Bloch *et al.* [10] evaluated a commercial fall detector (Vigi' Fall [122]) under real-life conditions on elderly patients and compared the results with simulated fall data from healthy young subjects. For the elderly, the study was conducted over a period of 20 months. Ten subjects over 75 years old with a risk of falls were recruited for their studies. For the young healthy volunteers, 14 subjects were recruited and laboratory experiments were conducted with a similar Vigi' Fall detector. The results showed a sensitivity and specificity of 62.5% and 99.5%, respectively, for the elderly. The results for the young volunteers had a sensitivity and specificity of 90% and 94%, respectively. From their results, Bloch *et al.* assert that the falls experienced by the elderly subjects are similar to those carried out in the laboratory environment by young healthy subjects. They attribute the lower sensitivity level in the elderly group to the inability of the carers to verify some of the falls.

Furthermore, Kangas *et al.* [49] compared real-life accidental falls by older people with falls in healthy middle-aged subjects in experimentation. Real-life falls (experienced by the elderly), such as forward, backward, sideways falls and fall-out-of-bed were compared with similar types of experimental falls performed by healthy middle-aged subjects. Fall events were divided into pre-impact and impact phases. A pre-impact phase was defined as a phase when a faller experiences a free-fall and an impact phase is when a faller makes contact with the floor and finally comes to rest. Twenty subjects (6 males and 14 females with mean age of 48±6.8 years) were recruited for the experimentation, with a 3D accelerometer strapped to their waists. Additionally, 16 elderly subjects (13 females and 3 males) with a mean age of 88.4±5.2 years participated. The experiment ran for 6 months and only 5 real-falls from 3 elderly subjects were recorded. The VM of acceleration was computed and results showed that four of the real-falls had multiple impact phases and a short pre-impact phase, which was similar to simulated falls. In addition, for fall-out-of-bed, both simulated and real-falls showed similar characteristics in that no pre-impact phase was observed, but an impact phase was recorded. Based on this evidence, Kangas *et al.* suggested that there are similarities between real-falls and laboratory simulated falls. Their study further suggested that real-life falls are often characterised by much higher readings during the impact phase compared to corresponding simulated falls because simulated fall are usually performed on soft surfaces.

Klenk *et al.* [55] compared the variation in acceleration and maximum jerk (the rate of change of acceleration) of 5 real backward falls of 4 elderly women (mean age 68.8±4.5 years) with corresponding signals of simulated backward falls by 15 young healthy subjects (mean age 24.1±1.91 years, 56% women). All 4 elderly women were suffering from Progressive Supranuclear Palsy (PSP) (a disease that gradually destroys nerve cells in the brain). For the simulated falls, 2 sets of experiments were performed.

1. Subjects were instructed to fall on their back onto a 15cm thick mattress as if they were a frail old person.
2. Subjects were instructed not to fall if possible, when released from a backward lean of around 30–40 degrees.

A Dynaport MiniMod data logger was used to acquire both the real-falls and simulated falls acceleration data. A fall phase was considered as 1.5 seconds before an impact was observed and the variance during this phase and the maximum jerk on each axis were used to describe the differences between real-falls and simulated falls. The median for both maximum jerk and variance in experiment 1 showed there was significantly more variations in real-falls than simulated falls. These variations can be attributed to the fact that patients used compensation strategies to prevent impact because their intention was not to fall (unlike in simulated falls). This trend was reversed in experiment 2. The median of variances of acceleration for simulated falls and jerk were much higher compared with real-falls. For subjects, the intention was to avoid a fall, hence the high variations. Though there are variations between real and simulated falls, Klenk *et al.* suggested that protocols should be designed to mimic real-falls.

In summary, in order to acquire data that are representative of real-fall data, protocols need to be designed in a way that prevents subjects from having control over the way they fall. Falls are sudden events, and often, fallers do not have control over how they fall. While it is be difficult to exactly recreate a real-fall, an attempt was made in this thesis to simulate falls as realistically as possible within the constraints of a laboratory environment. Four types of falls (forward, backward, left and right falls) were simulated. Two approaches were used in simulating falls:

1. Subjects were informed to throw themselves down onto a mattress.
2. A fall was induced by pushing a subject standing on a balance board onto a mattress. Subjects were blindfolded before they were pushed in order to prevent them from having control of the way they fall.

This approach of fall simulation allowed for data from both self-induced and externally induced falls to be acquired. By combining both types of fall, it is expected that algorithms that can more accurately detect falls are developed.

2.10 Summary

Fall detection is a well established area of research, with many commercial products and publications aimed at reducing the occurrence or impact of falls. However, most fall detectors are still affected by high FPRs and FNRs. This review discussed falls in the elderly, identified some of the commercially available fall detectors and gave an overview of fall detection systems designed. The overview described the sensors, data collection methods, subject types used to simulate falls and algorithms developed. The review shows that most fall detection algorithms are based on thresholds set by an observational analysis of fall data.

Due to the complex nature of human movement, thresholds set manually do not generalise well for new unseen subjects and fall types. This was evident from the evaluation performed in Section 2.8 in which the F-measure of existing systems is less than 90%.

An important aspect of developing algorithms that provide high accuracy is training and testing with the appropriate class of subjects and data. However, there are ethical challenges in recruiting the elderly and infirm for such experiments. Hence young and healthy subjects are often recruited. Section 2.9 discussed the experimental procedure and outcomes from previous research works that compared the differences and similarities between fall data from young healthy subjects and the elderly. Based on the understanding of the differences and similarities in falls between the elderly and the young, the protocols in this thesis were adapted to take into consideration these differences and similarities in fall data. The next chapter describes the experimental procedures and protocols in this research work.

Chapter 3

Data Gathering

In chapter 2, a review of the relevant literature was presented. This chapter describes the experimental protocols designed for the simulation of falls and Activities of Daily Living (ADL). When gathering data for training and evaluation of machine learning based algorithms, the steps are: i) design a data collection protocol, ii) identify appropriate hardware platform and sensors necessary for acquiring data, iii) recruit volunteers, iv) gather data, and v) use the data to evaluate the fall detection algorithm. This chapter presents the experimental design for data gathering and a summary of the datasets gathered. This is followed by an evaluation of a commercial fall detector to provide a baseline for the results in this thesis.

The rest of this chapter is structured as follows: Section 3.1 describes the experimental protocol used for data gathering. Section 3.2 presents a summary of the datasets gathered. Section 3.3 presents an evaluation of a commercial fall detector. Section 3.4 summarises the work in this chapter.

3.1 Experimental protocols

This section describes a protocol developed to gather data suitable for use in the development and evaluation of fall detection algorithms. A protocol describes a set of activities and events engaged with by subjects during data acquisition. These activities may be scripted or freeform. For an experimental protocol to be fit for purpose, the data gathered must be representative of the activities encountered during real-life system use. Falls are abnormal events that occur during normal daily activities and so the protocol was designed to simulate falls during normal daily activities.

A challenge encountered during the work was the acquisition of data relating to falls by the elderly. This is because of two primary reason: i) it is considered by many to be unethical to use elderly subjects when simulating falls due to the potential risk to their health and ii) only very few real falls occur each year per elderly person (albeit with severe consequences), leading to a lack of data for non-simulated falls. Therefore, in the work here, falls and ADL were simulated by young healthy volunteers. This approach is in-line with the methods used most commonly in the literature.

Three datasets (D1, D2, and D3 as described in Section 3.2) were acquired during three distinct groups of trials, involving a total of 50 subjects.

The remainder of this section describes the subjects recruited for data gathering (Section 3.1.1), data collection and protocols (Section 3.1.2), and trial groups 1, 2 and 3 (Sections 3.1.3, 3.1.4, and 3.1.5 respectively).

3.1.1 Subjects recruited for data gathering and hardware platform

Fifty young healthy subjects (shown in table 3.1) were recruited for this work. Before subjects were recruited, a medium risk ethical approval was granted by the ethics committee at Coventry University. Participation was completely voluntary and consent forms were signed by each participant at the start of each trial. Verbal explanations were also provided to each subject at the start of each trial in order to ensure that participants understood what was required of them. Six females and 44 males were recruited,

Table 3.1: Subjects recruited for the data gathering trials.

Protocol 1				
Subjects	Age (years)	Height (cm)	Weight (Kg)	Gender
S1_Pr1	33	176	70	M
S2_Pr1	25	162	80	M
S3_Pr1	25	165	65	M
S4_Pr1	21	166	75	M
S5_Pr1	26	167	61	M
S6_Pr1	21	170	60	M
S7_Pr1	25	189	100	M
S8_Pr1	23	175	100	M

Protocol 2				
Subjects	Age (years)	Height (cm)	Weight (Kg)	Gender
S1_Pr2	23	174	75	M
S2_Pr2	19	168	84	M
S3_Pr2	21	185	82	M
S4_Pr2	24	172	108	M
S5_Pr2	20	168	59	M
S6_Pr2	21	176	65	M
S7_Pr2	25	170	70	M
S8_Pr2	21	174	65	M
S9_Pr2	21	187	65	M
S10_Pr2	30	175	75	M
S11_Pr2	23	168	67	F
S12_Pr2	25	175	89	M
S13_Pr2	24	164	70	M
S14_Pr2	22	170	62	M
S15_Pr2	24	175	86	M
S16_Pr2	18	171	56	M
S17_Pr2	22	176	64	M
S18_Pr2	21	175	68	M
S19_Pr2	26	179	88	M
S20_Pr2	19	170	80	F
S21_Pr2	38	173	75	M
S22_Pr2	51	181	80	M
S23_Pr2	31	170	60	M
S24_Pr2	21	177	60	M
S25_Pr2	23	173	60	M
S26_Pr2	25	163	58	F
S27_Pr2	20	164	51	F
S28_Pr2	21	175	67	M
S29_Pr2	22	165	78	M
S30_Pr2	24	162	59	M
S31_Pr2	27	177	72	M
S32_Pr2	22	173	75	M

Protocol 3				
No	Age (years)	Height (cm)	Weight (Kg)	Gender
S1_Pr3	23	175	90	M
S2_Pr3	21	169	60	F
S3_Pr3	24	150	43	F
S4_Pr3	21	181	58	M
S5_Pr3	23	164	61	M
S6_Pr3	30	183	99	M
S7_Pr3	23	170	63	M
S8_Pr3	31	171	59	M
S9_Pr3	21	176	57	M
S10_Pr3	22	170	65	M

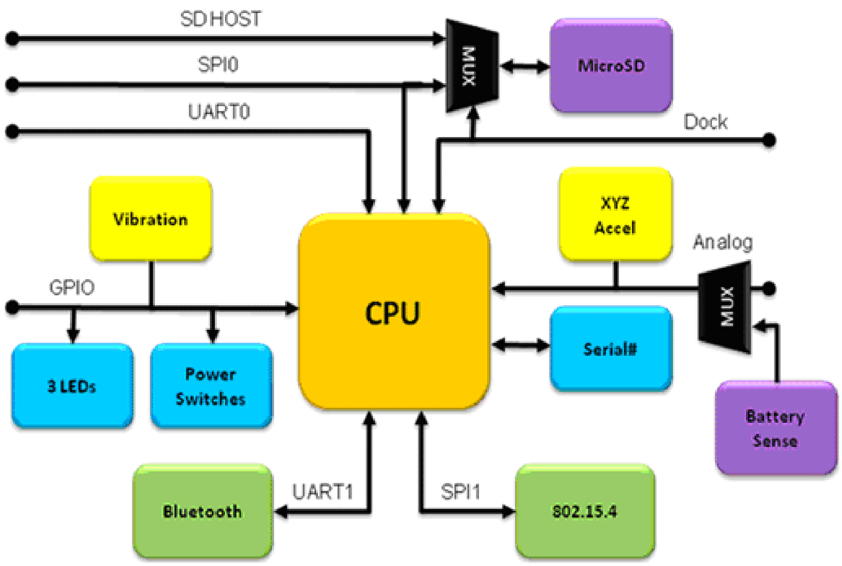

Figure 3.1: SHIMMER board and integrated devices

the youngest subject being 18 years and oldest 51 years old. The mean and standard deviation for the age, height and weight were 24.2 ±5.4 years, 172.1 ±7.0 cm and 70.8 ±13.8 kg respectively. These subjects followed the protocols described in the next section.

Hardware platform

The hardware platform worn by subjects during data acquisition is the SHIMMER, an acronym for Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability. Figure 3.1 shows SHIMMER block diagram and its integrated devices. Two SHIMMER sensor nodes strapped to the chest and thigh of subjects were used for data acquisition and transmission from subjects to a remote PC. Each sensor node consists of a 3D accelerometer and 3D gyroscope, a Bluetooth device and an MSP430F1611 microcontroller device. The SHIMMER sensor node is shown in Figure. 3.2, Page 28, weighs 27g and has a dimension of (53 x 32 x 19) mm. The Bluetooth device (Rovering Network RN-42) has a range exceeding 10 m, a default transmission rate of 115 kbaud, and is a class 2 Bluetooth module.

The tri-axial accelerometer (MMA7260Q) from Freescale Semiconductor has a range up to $\pm 6g$. A MicroElectroMechanical Systems (MEMS) accelerometer behaves as a mass on a spring which is displaced when it experiences an acceleration. The displacement of the mass is measured to determine the acceleration of the sensor. An accelerometer at rest measures an acceleration of $g = 9.81$ m.s^{-2} ($1g$) straight upward due to its weight and an accelerometer in free-fall measures zero [131, 106].

The tri-axial gyroscope consists of an InvenSense IDG-500 dual-axis (X, and Y) and ISZ-500 single axis (Z) angular rate sensor MEMS from Freescale Semiconductor, with a full scale range ±8.7 rad.s^{-1}, and a sensitivity of 110 mV.rad^{-1}.s. The operating principle of MEMS gyroscopes is based on using a vibrating mechanical elements to sense rotation. When angular velocity is applied to a gyroscope, two masses within the sensor oscillates, thus making the Coriolis force (Coriolis force is a force experienced in a rotating reference frame and is proportional to the rate of rotation) on each mass to act in opposite direction, which results in change in capacitance [131, 93].

3.1.2 Data collection and protocols

Acceleration and gyroscope data (in three dimensions) was gathered from two Shimmer sensor nodes placed on each subject's chest and thigh (as shown in Figure 3.2). Data were sampled at 100 Hz and transmitted via Bluetooth to a PC for further processing. Falls and ADL were annotated post-hoc using

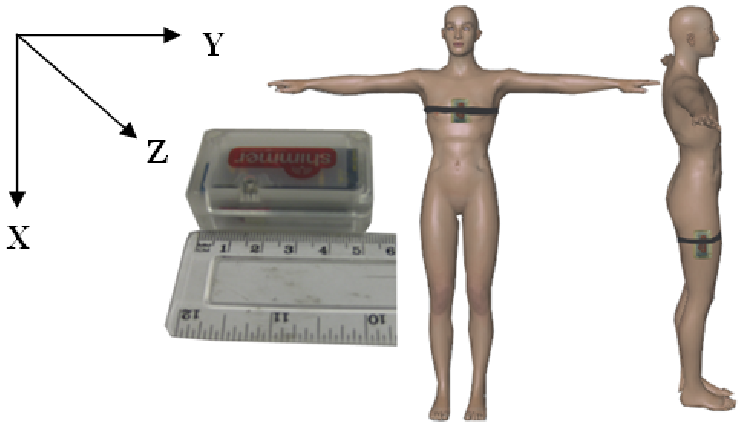

Figure 3.2: Placement of Shimmer sensor nodes on experimental subjects.

a custom application written by the author in Labview. Before the start of each trial, an identifiable event was introduced into the data by striking the two nodes together. This then allows for accurate time-alignment of the data for annotation and processing. An overview of the data gathering set-up is shown in Figure 3.3. The data collection procedure (see Figure 3.4) begins with the design of the experimental protocol. The definition of the protocol helps to identify the various activities to "simulate" and which subjects to recruit. In the next step, subjects were recruited and instrumented with sensors. Following this, subjects were asked to perform various falls and daily activities as per the protocol. The resulting data is collated, analysed and used to develop the algorithms presented in this thesis.

The protocols are as follows:

- Protocol 1 involved the simulation of four types of falls (forward, backward, left and right falls) and a set of ADL. The data gathered using this protocol served as a source of initial insight into the fall data algorithm development. This protocol and the trials conducted are discussed further in Section 3.1.3.

- Protocol 2, similar to Protocol 1, involved the simulation of four types of falls. In addition, Protocol 2 also included the simulation of loss of balance (near-falls) and falls induced by applying a lateral force to the subject. Near-falls are events that occur as a result of stumbles, trips or collisions with obstacles. These events do not necessarily result in falls, but may produce acceleration signals similar to falls before the subject recovers from the loss of balance. Real falls are often unintentional and fallers are not normally in control of their bodies when they fall. Thus, some of the falls were simulated by applying a lateral force on subjects such that they had less control over how they fell. For this protocol, the expectation was that a mix of fall and near-fall types would provide data which were suitable for the development and evaluation of fall detection algorithms. This protocol and the trials conducted are discussed further in Section 3.1.4.

- Protocol 3 involved ascending and descending a staircase at self-selected pace. Climbing a staircase is part of a normal daily activity, which is characterised by fast movement of the limbs and requires a high level of coordination. In addition, it produces high acceleration signals, which can be similar to falls and, thus, may cause a fall detection algorithm to output false positives. This protocol and the trials conducted are discussed further in Section 3.1.5.

The standards in medical field for fall prevention and detection was discussed in Section 2.1.4, Page 8. However these standards have been proven not to be effective in detecting falls [71, 39, 86]. Therefore, the approach used in protocol design in this thesis is based to methods proposed in research in which

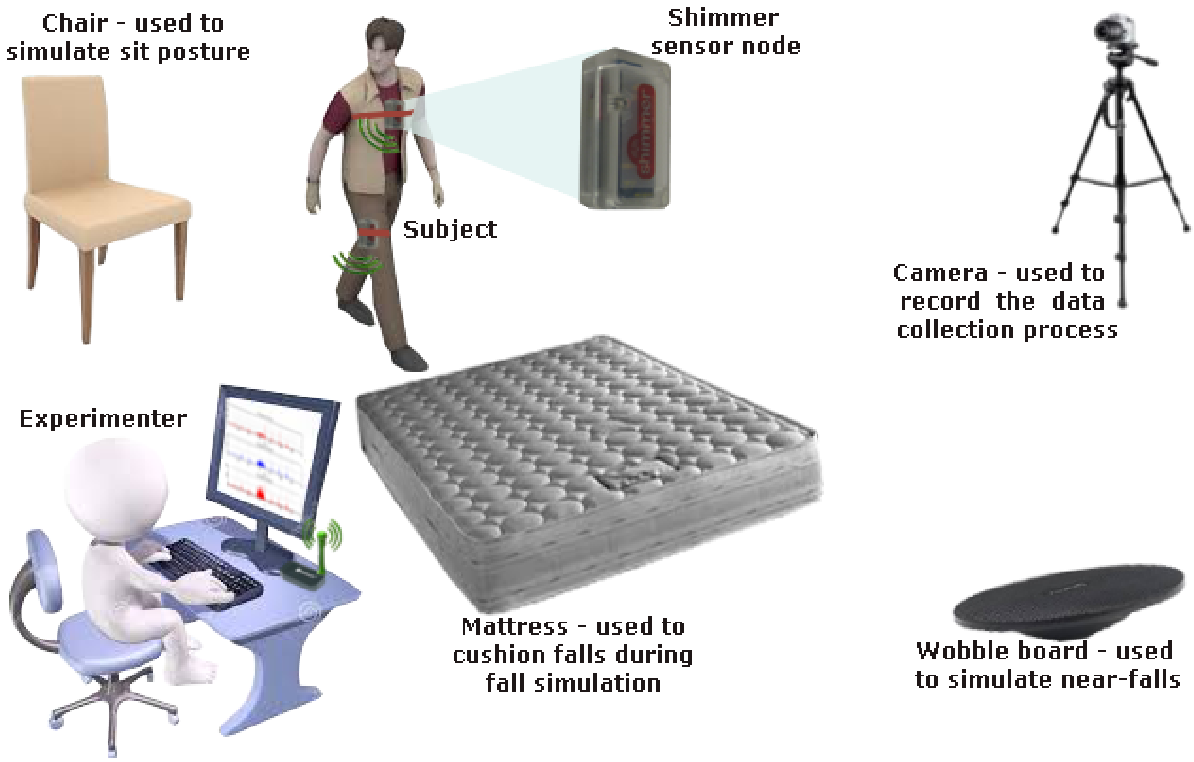

Figure 3.3: Data collection set-up

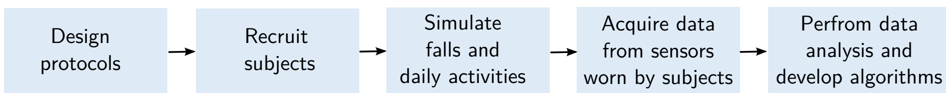

Figure 3.4: The data collection and system development procedure

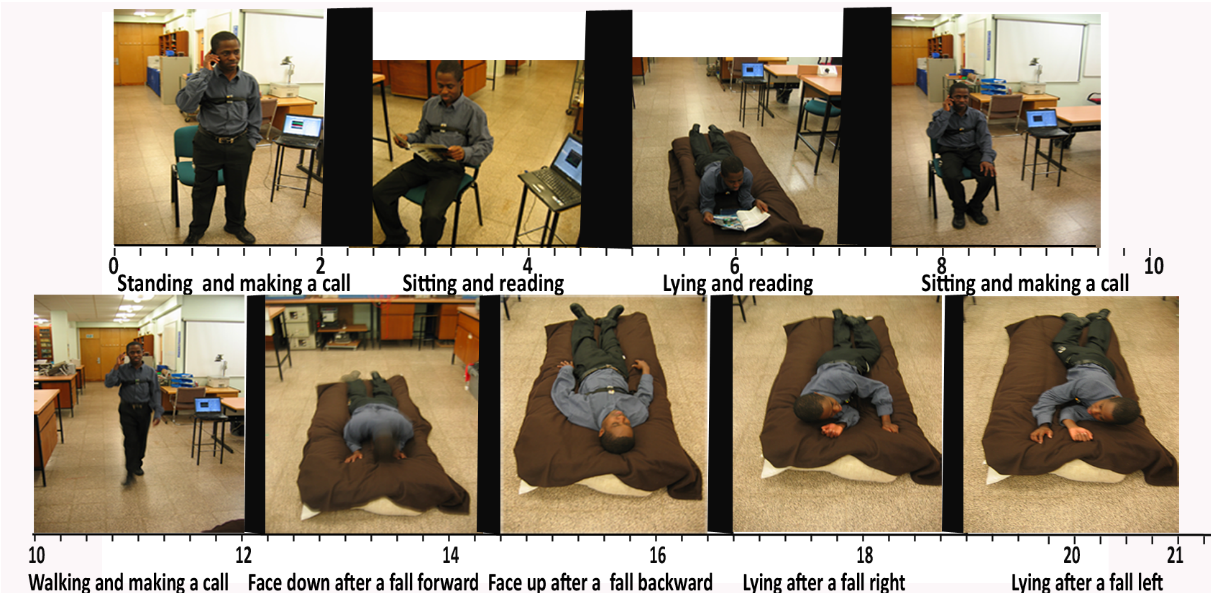

Figure 3.5: Protocol 1 showing ADL and falls (time scale in mins).

subjects were recruited to act-out falls and ADL scenarios [12, 15, 58]. Some of the reasons for choosing this approach include:

- The falls acted in a laboratory environment are similar to those experienced by fallers under real-life scenarios as discussed in Section 2.9, Page 23.
- A wide range of activities and events required for algorithm development can be included in protocols acted in a laboratory.

The next sections present a detailed description of each protocol and the trials conducted.

3.1.3 Protocol 1

Eight healthy young subjects (as shown in Table 3.1, Protocol 1) took part in an experiment which consisted of ADL and four types of falls (fall forward, fall backward, and falls toward the left and right). The protocol is summarised in Fig. 3.5. Each subject performed the protocol twice, for a total time of 42 minutes per subject.

Activities of Daily Living

Standing, sitting, lying and walking were maintained for 2 minutes each (including time to change posture). It was assumed that in real-life people will normally engage in activities such as making phone calls, reading books, or talking to other people while maintaining various postures. Therefore, in order to gather realistic ADL data, the protocol incorporates these activities. The ADL portion of Protocol 1 therefore consists of: i) standing while using a phone, ii) sitting on a chair while reading a book, iii) lying posture while continuing to read a book, iv) sitting while using a phone, and v) walking while using a phone.

Fall events

Subjects were asked to deliberately fall onto a 25 cm thick cushion and then change from lying to sitting after a few seconds, remaining on the cushion. The time from first impact on the cushion until the subject finally stood up after a fall and the transition to sitting was around 2 minutes. This process was performed for fall forward, fall backward, and falls to the left and right.

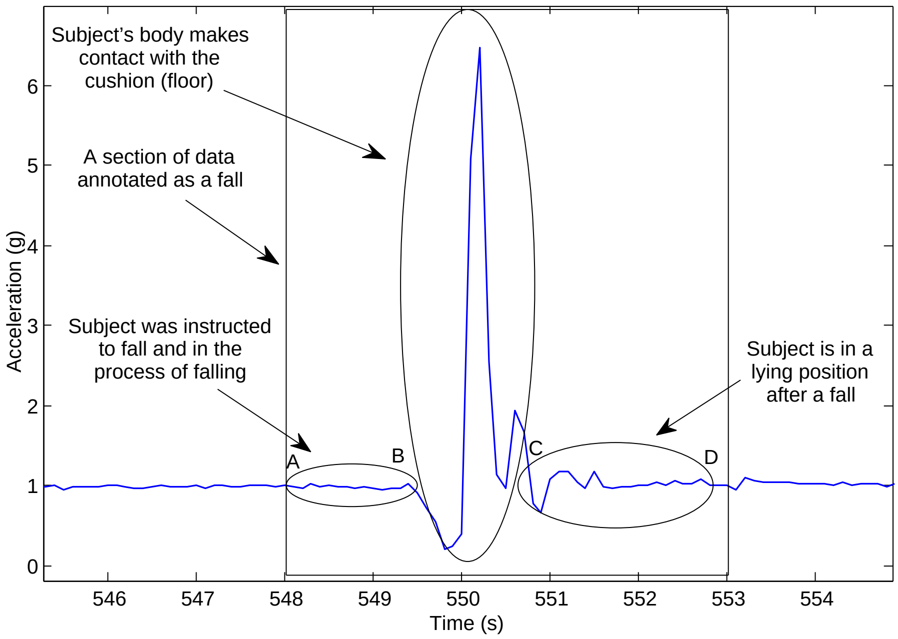

Figure 3.6: Fall annotation for a single fall event.

Falls annotation

The annotation for a single fall event is shown in Figure 3.6. Each fall is considered to take 5 seconds. From the figure, the period annotated as a fall is from 548 s to 553 s. From point A to point B, the subject has started to fall and has not yet made contact with the floor. Between points B and C, the subject's body makes an impact with the cushion on the floor and high acceleration values are recorded. After a fall has occurred, the subject remains in a lying position from point C to D. Though point A to D corresponds to a fall, only point B to C shows the high acceleration that identifies the fall.

Examples of activities and events simulated during data gathering are shown in Figure 3.7. The figure shows that some near-falls and transitions generate high acceleration signals, thus making it difficult to discriminate between falls and events that are not falls.

Lessons learnt

Following the trials conducted using Protocol 1, several ways in which the data gathering and annotation process could be improved were found. The enhancements to the process considered were:

- *Implementation of an activity-intensive protocol which embeds falls in a typical set of daily activities.* This approach involves the design of protocols that defines a set a of daily activities during which falls can occur. For instance, a subject can be walking, then sit down, then stand up, then fall, and finally sit on the floor. The data acquired will therefore consist of a combination of static postures, transitions, and fall events, with the aim of better reflecting the situations in which falls may occur.

- *More precise annotation of the fall event.* During data gathered via Protocol 1, each fall event was annotated as a 5 second window of data. However, it was observed that the fall process took on average 3 seconds. This means that periods of data not corresponding to falls are labelled as falls, negatively impacting the ability of a machine-learning algorithm to discriminate between normal activities and falls. Hence, in order to provide data suitable for this purpose, the annotation must

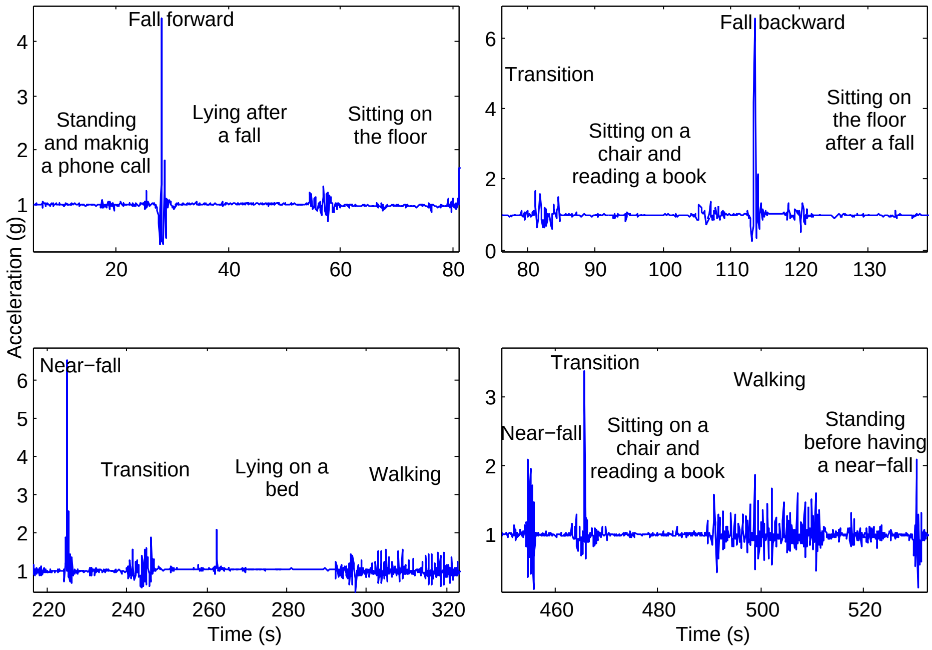

Figure 3.7: Activities and events simulated during data gathering

be more precise. For Protocol 2, each trial was recorded on a video camera in addition to the annotation performed during the trial.

- *Improvements in fall simulation and the inclusion of events (near-falls) that are similar to falls in terms of acceleration characteristics.* Real-life falls are always unintentional and fallers are not in control of how they fall. Hence, in Protocol 2, falls were simulated in a manner that prevented subjects from being in control of how they fell. Near-falls were also included as they resemble falls in some respects and thus may be difficult to distinguish.

3.1.4 Protocol 2

Protocol 2 expanded on the process employed for Protocol 1 by resolving the issues described in the previous section. Additionally, more activities were introduced and the time spent on each activity was reduced to between 5–10 seconds. By introducing more activities and reducing time spent on each activity, the imbalance in data between falls and ADL was reduced. Furthermore, loss of balance events (near-falls) were introduced. In real life, near-falls occur more often than falls, with the subject able to recover and regain their balance. Acceleration signals during near-falls often have high amplitudes similar to falls. Falls were extended to include several postures immediately following the fall, not just lying down. Figure 3.8 shows the activities for Protocol 2.

Other than the different activity composition, the other major change was that the trials were recorded using a video camera. The advantages of this are:

- Camera-synchronised data acquisition allowed for more accurate post-hoc annotation of the gathered data.

- Video recordings allow investigation of classification results. For example, if a classifier fails to classify data from a specific subject correctly, video footage can be re-examined in order to gain insight into why this occurred.

Before the start of each trial, an identifiable event was introduced into the data by striking the two nodes together in view of the camera. This introduced an identifiable event into the data from each node and the time of striking was captured on the camera. At the end of the trial, this was repeated.

Data gathering protocol Thirty-two young healthy subjects (as shown in Table 3.1, Protocol 2) were recruited for these trials. Each subject underwent nine distinct activity sets as follows:

1. Subjects were instructed to stand and make a phone call for 10 seconds, then fall forward and stay lying for 5 seconds after the fall. They then sit up on the floor for another 5 seconds.

2. Subjects were instructed to sit on a chair and read a book for 10 seconds, then stand up and fall backward, either falling directly into a sitting posture or sitting up immediately after the fall.

3. Subjects were instructed to stand for 10 seconds and then simulate a near-fall by being pushed gently from a balance board while blindfolded. After the near-fall, subjects were instructed to lie on a bed and read a book.

4. Subjects were instructed to walk for 10 seconds while making a phone call, then fall forward either directly into a crouching position or crouching immediately after the fall. They crouched for 5 seconds and then sat on the floor for another 5 seconds.

5. Subjects were instructed to sit on a chair for 10 seconds while making a phone call, simulate a near-fall by being pushed gently from a balance board, then sit on a chair and read a book.

6. Subjects were instructed to walk for 10 seconds, simulate a near-fall by being pushed gently from a balance board, then fall towards the right either directly into a crouching posture or crouching immediately after the fall. The crouch was maintained for 5 seconds, followed by sitting for 5 seconds.

7. Subjects were instructed to fall to the left and remain lying down for 10 seconds.

8. Subjects were blindfolded and instructed to stand on a wobble board. While they tried to balance, they were pushed from behind to fall forward onto a cushion and remained lying down for 10 seconds.

9. Subjects were blindfolded and instructed to stand on a wobble board. While they tried to balance, they were pushed from the front to fall backward onto a cushion and remained lying down for 10 seconds.

3.1.5 Protocol 3 - Ascending and descending of stairs

Protocol 3 involved acquiring data from subjects during the ascending and descending of a staircase which consists of 20 steps. The ascending and descending of the stairs was performed 15 times at self selected pace. Ten young healthy volunteers (as shown in Table 3.1, Protocol 3) were recruited and instructed not to rest their hands on the stair handrail while ascending or descending the stairs. Walking on the stairs is a common ADL activity and it is important to be able to discriminate between walking on the stairs and falls. Walking on the stairs is a potentially dangerous and a demanding task for an elderly person [101, 60], and shows higher variation in peak-peak amplitude than static activities.

3.2 Summary of datasets

The datasets gathered through the protocols described here are essential for building fall models using a machine learning approach due to the complex nature of human movement. A summary of the trials performed is presented in Table 3.2. Falls and ADL were simulated in both D1 and D2, while no falls were simulated in D3. A major challenge in D1 is data imbalance between ADL and falls, due to the much shorter duration of the latter. In order to reduce the data imbalance, the amount of time spent in each

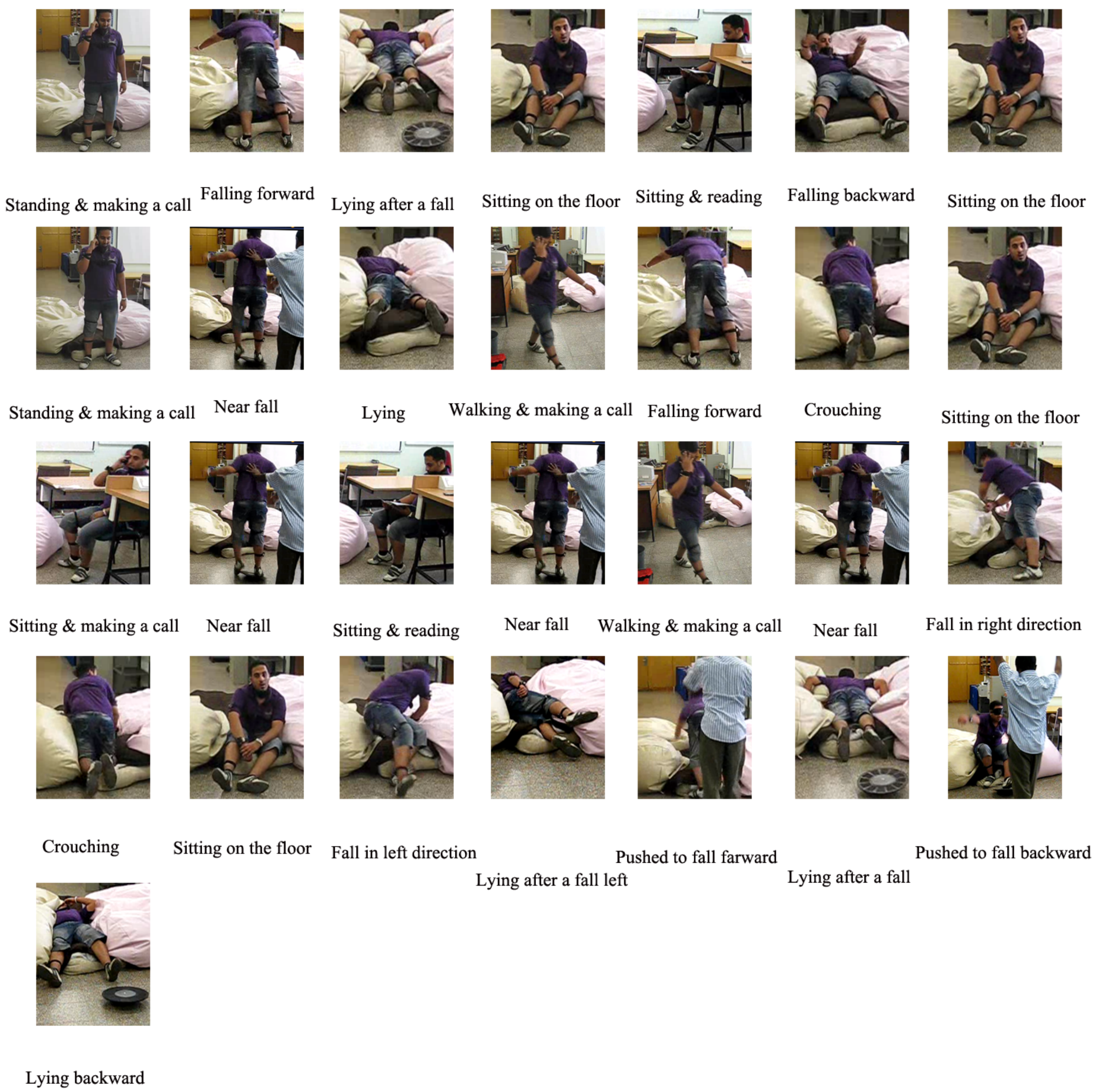

Figure 3.8: Activities and events during data gathering for Protocol 2.

Table 3.2: Summary of datasets gathered.

Dataset	Protocol	Subjects	Time/subject (mins)	Yield (%)	Trials/subject	Falls/subject	Near-falls/subject
D1	1	8	42	> 99.9	2	8	0
D2	2	32	23	> 99.9	2	14	6
D3	3	10	4	100	1	0	0

activity for Protocol 2 was reduced from 42 minutes to 23 minutes compared to Protocol 1. Near-falls were simulated in Protocol 2.

D1 was used for developing and evaluating Algorithm I and Algorithm II (see Sections 4.2 and 4.3). D2 was used in developing and evaluating Algorithm III and IV (see Section 4.4,and 5). D3 was used to evaluate Algorithm IV (see Section 5.6.2).

3.2.1 Discussion on data collection

The experiments described in Section 3.1.3 through 3.2 set a foundation for the development and evaluation of algorithms that can deliver high accuracy by providing access to good fall simulation data. The use of young healthy volunteers for fall simulation in this thesis is similar to the approach commonly used in literature for fall data gathering [1, 68, 134, 37, 83, 11, 50]. Although real-life fall data from the elderly was not available, experiments were designed to mimic real-life falls within the constraints of a laboratory environment. The data gathered were based on continuous scripted activities engaged in by subjects; data were not truncated.

Two approaches were employed in fall simulations: i) subjects voluntarily fell onto a mattress as realistically as possible and ii) falls were induced by blindfolding and pushing subjects onto a mattress. For the induced falls, subjects were less in control of the way they fell; thus replicating a lack of control normally experienced by fallers during real-life falls. Furthermore, protocols were designed to include activities such as standing, sitting, walking, lying and ascending and descending a staircase which are often encountered on a daily basis. During normal daily activities, some activities may trigger loss of balance but not necessarily lead to falls. However, such events produce acceleration characteristics which are similar to falls. The trials conducted provide data for such events.

3.3 Evaluation of a commercial fall detector

An existing commercial fall detector from one of the leading suppliers of assisted living technology in the UK (the Tynetec fall detector, shown in Figure 3.9), was worn by 22 subjects in order to assess the strengths and weaknesses of the device. The fall detector was worn on the waist of each subject during data acquisition and the integrated alarm used to signal falls was listened for and logged (the device does not allow access to the raw data). The number of falls recorded manually was checked against the total reported by the device at the conclusion of each trial. The metrics used to evaluate the fall detector were precision, recall and F-measure.

Ideally, fall detectors should not have any False Positives (FPs) or False Negatives (FNs) because it is important that all falls are detected and no false alarms are triggered. The signalling of false alarms or failure to detect falls will impact on the uptake of such devices due to lack of trust in them. Therefore, the Tynetec fall detector was evaluated using the same protocols as described earlier.

Prior to evaluation, a sensitivity level for the fall detector required selection. The fall detector has 5 levels of sensitivity, with level 1 being the most sensitive and level 5 the least sensitive. Initial testing of the detector showed that the most sensitive detection level (level 1) was required in order to capture any of the fall types considered here.

The evaluation was performed based on the protocols described in Sections 3.1.4 and 3.1.5. A summary the results can be found in Table 3.3. Following Protocol 3, all 10 original volunteers wore the fall detector while ascending and descending a staircase. No falls were simulated, however 2 false alarms were triggered. A further evaluation was conducted with 22 volunteers selected at random from those that previously undertook Protocol 2. Only 36% of the falls simulated were classified correctly (giving an F-M of 50%). The fall detection had a precision of 81% and a recall of 36%, meaning that the system is more likely to miss falls than trigger false alarms.

Figure 3.9: Tynetec fall detector

Table 3.3: Summary of Tynetec fall detector performance. **precision, recall, and F-measure are 0 due to the lack of falls. The number of false positives and false negatives are 26 and 198 respectively.*

Scenario 3								
Evaluation	Fall detector sensitivity level	No of subjects	No of falls	Precision (%)	Recall (%)	F-Measure (F-M) (%)	Activities	Time taken (minutes)
A	1	10	0	*	*	*	Ascending and descending stair case with 20 steps, 15 times per subject	38
B	1	22	308	80.9	35.7	49.5	Falls and ADL	552

3.4 Summary

With the aim of gathering data suitable for machine learning based fall detection algorithm, three protocols were designed. Fifty young healthy volunteers were recruited to take part in the experiments. The protocols were designed to mimic activities and events performed on a regular basis and in a typical home environment. Two Shimmer sensor nodes strapped to the chest and thigh (see Figure 3.2) were used to acquire data relating to acceleration and angular velocity of subjects and sampling was performed at 100 Hz.

In addition, a commercial fall detector was evaluated under the same protocols. The results of the evaluation show that the fall detector missed many falls and triggered a number of false alarms. It is expected that the algorithms developed here will exceed the performance of this detector.

The next chapter describes the development and evaluation of three fall detection algorithms implemented in the work here.

Chapter 4

Fall Detection Algorithms

The previous chapter presented the data gathering protocols for simulation of Activities of Daily Living (ADL) and falls and the resulting datasets gathered. This chapter presents the development and evaluation of three fall detection algorithms using the gathered data.

Many of the fall detection algorithms in the papers reviewed in Chapter 2 depended on thresholds determined via observational analysis of fall data (see Section 2.5.3). However, these algorithms are typically marred by high levels of False Positives (FPs) and False Negatives (FNs) due to the complex nature of human movement. Three approaches are proposed here, two of which are based on automatic selection of parameters using training data and one of which is based on thresholds selected via analysis of the gathered data. In order to establish the best approach for fall detection, three different algorithms were investigated:

1. Decision tree (C4.5)
2. Logistic regression
3. Dot-product based

The contribution in this chapter is:

- The evaluation of three algorithms for fall detection, demonstrating that when using traditional annotation methods and point-in-time input features (specifically Vector Magnitude here) they do not provide a sufficiently high accuracy. The baseline accuracy considered here is an F-measure of at least 90%.

This chapter is structured as follows: Section 4.1 gives an overview of the data pre-processing and conditioning implemented. Sections 4.2, 4.3, and 4.3 describe the implementation and evaluation of the decision tree, logistic regression algorithm, and dot-product algorithms respectively. Finally, Section 4.5 presents a summary of the work in this chapter.

4.1 Data pre-processing and conditioning

Prior to the gathered data being used to train and evaluate fall detectors, the acceleration and angular velocity data were first pre-processed. The pre-processing performed included resampling, annotation, scaling, filtering and feature extraction.

Annotation Two types of annotations were used as described in Section 3.1.3 and 3.1.4 for Protocols 1 and 2 respectively. In Protocol 1 each fall event was annotated as a 5 second window of data, while in Protocol 2 each fall was annotated by an experimenter based on the start and end of the fall cross-checked against video recordings.

Scaling The data scaling for acceleration and angular velocity converts the raw sensor data into units of g ($1\ g = 9.81\ \mathrm{ms^{-2}}$) and degrees/second, respectively. This is described in Appendix A.1.

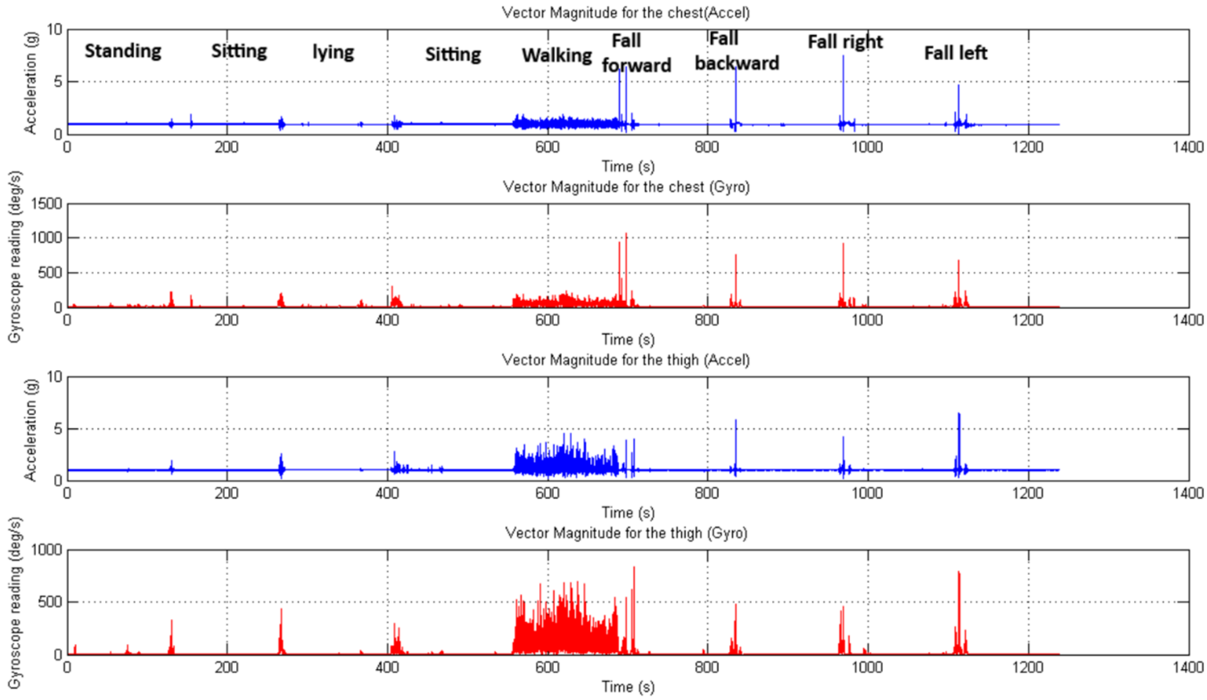

Figure 4.1: VM for falls and ADL.

Resampling The data was resampled at 10 Hz from the original rate of 100 Hz.

Filtering Filters were implemented to i) remove noise from the acquired sensor data and ii) compensate for gyroscope drift. In the latter case, a high-pass filter was applied to the angular velocity data from the gyroscope. The gyroscope data is prone to drift and, during integration, this makes the angle derived from angular velocity continue to change even when the sensor is stationary. The angular velocity was high-pass filtered at 0.05 Hz with a second-order Butterworth filter.

Feature extraction When detecting falls, it is not necessarily the acceleration or rotation of the body in any specific dimension that is important. Instead, it may be more suitable to consider some aggregate of the 3 dimensional sensor output. For this reason, Vector Magnitude (VM) is used as a data feature, calculated as $\sqrt{x^2 + y^2 + z^2}$ where x, y and z are the sensor readings for each axis. A demonstration of VM computed for the acceleration and angular velocity is shown in Figure 4.1. For the simulated fall events, high values can be observed. However, all fall events do not generate distinct high values and, occasionally, ADL may generate high acceleration values. In addition, human movement is complex and falls may differ considerably from subject to subject. For this reason, a machine learning approach (which can generalise a detector to give correct results for unseen subjects) is expected to provide a high accuracy and is the focus of the detectors presented here.

4.2 C4.5 decision tree based fall detection algorithm

This section describes the C4.5 Decision Tree (DT) algorithm and presents an implementation and the results of evaluation. Classifiers are generated here using the Waikato Environment for Knowledge Analysis (WEKA) tool kit. The C4.5 DT training algorithm (see Algorithm 4.1) receives data and features (called attributes) as input along with the expected output class. It creates nodes by computing the information gain for each attribute and then labels the node with the attribute with the highest information gain. This results in a binary tree that consists of a root node, internal nodes, branches and

Algorithm 4.1 C4.5 Decision Tree training algorithm.

1. Create a node N
2. If : all sample belong to the same classification

   Then: return a leaf node labelled with that classification
3. Else if: attribute-list is empty

   Then: return a leaf node with majority class
4. Else: select the best-attribute with the highest information gain from attribute-list and update attribute-list (attribute-list - best-attribute)

   Then: label node with that attribute
5. For each: possible sample of best-attribute
6. Create branches from the node for the best attribute which corresponds to each sample
7. If: sample is empty

   Then: Return a leaf node with majority vote
8. Else: attach a node

Information Gain is a measure used to select the best attribute to split on.
The expected information needed to classify a given sample is: $(I) = -\sum_{i=1}^{c} P_i log_2(P_i)$
c is the distinct classes that exist
P_i is the probability of having a class label given as: $\frac{NoOfaClass}{SizeOfDataSample}$
The probability of getting an attribute value out of the whole data sample is: $\frac{Occurence_T}{SizeOfDataSample}$
$Occurence_T$is the total number of occurrence of that value in an attribute.

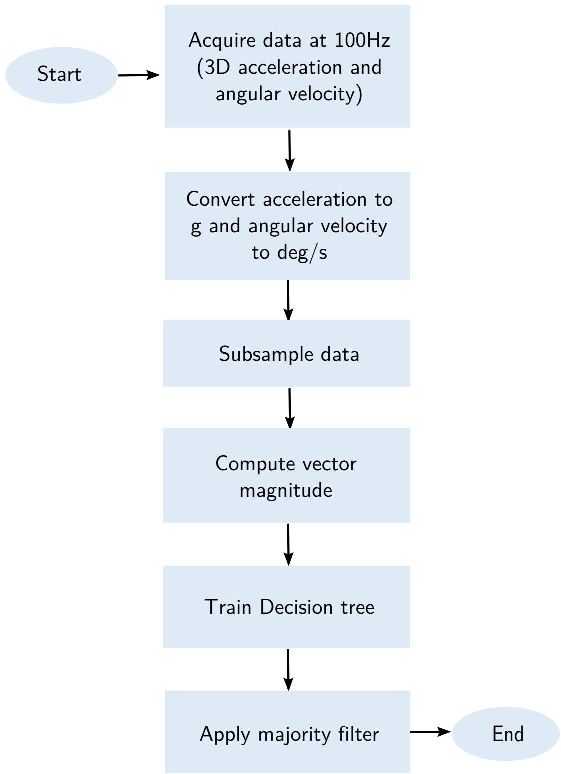

Figure 4.2: A flow chart showing an overview of the decision tree based fall detection algorithm.

leaf nodes. The root node is the top-most node in a tree, the internal nodes describe tests on selected attributes, the branches denote the outputs of each test, and the leaf nodes represent the output classes. The input attributes used here are the raw acceleration and angular velocity data from the sensors, along with the VM for acceleration and angular velocity. The output of the DT is fall or no-fall decision (1 or 0 respectively). A detailed description of the C4.5 algorithm can be found in Russell and Norvig [75, 102]. While the training process can be computationally intensive for large input datasets, decision trees are trivial for classification as they consist only of threshold comparisons. The following subsections discuss i) the implementation of decision trees in the work here and ii) the evaluation results.

4.2.1 Implementation

Features The features used here were: i) x, y and z axes for acceleration and angular velocity and ii) VM for acceleration and angular velocity. These features were computed for both the chest and thigh sensor nodes.

Datasets Dataset 1 (D1) using Protocol 1 (8 subjects total, see Table 3.1).

The output of the trained DT is filtered using a majority vote scheme with a non-overlapping window of 8 samples (0.8 seconds). The size of the window was determined via inspection of the data in relation to the duration of falls. The rule for majority voting is that for a window of data, if the majority of samples of data within that window is classified as a fall then the whole of that window is considered a fall, otherwise that window is considered as a no-fall. This approach effectively “smooths” the output of the detector, avoiding rapid changes in output for sections of data with a mix of classifications. A block diagram overview of the decision tree based algorithm is shown in Figure 4.2.

Table 4.1: Summary of fall classification for decision tree based algorithm at macro-events level.

Trained subjects	Avg. TP (4 falls)	Avg. FN (4 falls)	Avg. FP (21 mins)
7	3.69	0.31	6.06
6	3.59	0.41	16.50
5	3.53	0.47	8.08
4	3.60	0.29	11.00
3	3.52	0.48	13.00

4.2.2 Evaluation and results

The performance of the decision tree based algorithm was evaluated both i) at macro-events level, that is, the count of falls that occurred during experimentation and also ii) with regard to the match between the annotation and the detector output. For the purpose of the macro-event level evaluation, the detector was said to have detected a given fall if it outputted any "fall" classification during the annotated fall window (7 classifications at 1.25 Hz for a 5 second fall window), this is logged as True Positives (TPs). Any occurrence of a fall decision outside the annotated fall windows was considered a FP. Conversely, a window annotated as a fall during which no fall decision was output, was considered a FN.

Firstly, the fall detector was evaluated at the macro-event level. A total of 64 falls were performed by the 8 subjects, over the course of 42 minutes per subject. The number of correctly classified falls varied from subject to subject—leave one subject out cross-validation resulted in 5 subjects having all falls identified while the remaining 3 subjects had 5–7 of their 8 falls correctly identified. The number of FPs also varied from subject to subject, with a minimum of 3 and a maximum of 26. "Leave N subject out" cross-validation was also performed, the results of which are shown in Table 4.1. Given the nature of the experimental protocol (with a fall occurring on average every 5.25 minutes of experimental time) and the expectation that falls in elderly may occur with a frequency of 1 in 24 hours at most, one interpretation of the results is to calculate the frequency of FPs and FNs for a 24 hours period. The system is predicted to produce, over a 3 days period, approximately 5 FPs and will generate a FN every 12 days approximately.

The algorithm was also evaluated in terms of individual tree outputs versus the data annotation. Figure 4.3 shows detailed results from Leave N subject out cross-validation. Training with 7 subjects resulted in a mean precision, recall, and F-measure of 81.8%, 92.2%, and 86.4% respectively. The exact impact of varying training size can not be determined as there is no clear effect on the results.

Overall, the results show that the use of raw sensor data and VM with a decision tree based algorithm provide good fall detection accuracy, though the performance of the algorithm in terms of F-Measure (F-M) is not as high as the required baseline performance identified in Section 2.8 (90%).

4.3 Logistic regression based fall detection algorithm

Logistic regression (described by Field [32] and Kutner *et al.* [57]) allows categorical outcomes to be predicted based on continuous or categorical input variables. Equation 4.1 demonstrates logistic regression.

$$P(Y) = \frac{1}{1 + e^{-(b_0+b_1X_1+b_2X_2+\dots\dots\dots\dots+b_nX_n)}} \tag{4.1}$$

From Equation 4.1, the algorithm predicts the probability of a fall $P(Y)$ occurring considering the predictor variables X_1, X_2, ... X_n. The predictor variables are the input attributes, in this case, acceleration data for the three axes, the angular velocity for the three axes and the VM for acceleration and angular velocity. Finally b_0, b_1, b_2, ...b_n are the regression coefficients. The relationship between the output variable $P(Y)$ (the probability of a fall detected) and predictor variables (acceleration and angular velocity data) is not linear because the output variable is categorical and the inputs are continuous. $P(Y)$ is a probability output value which varies between 0 and 1. The values close to 0 are less likely to occur and values close to 1 more likely to occur. A summary of the logistic regression algorithm is given in Figure 4.4.

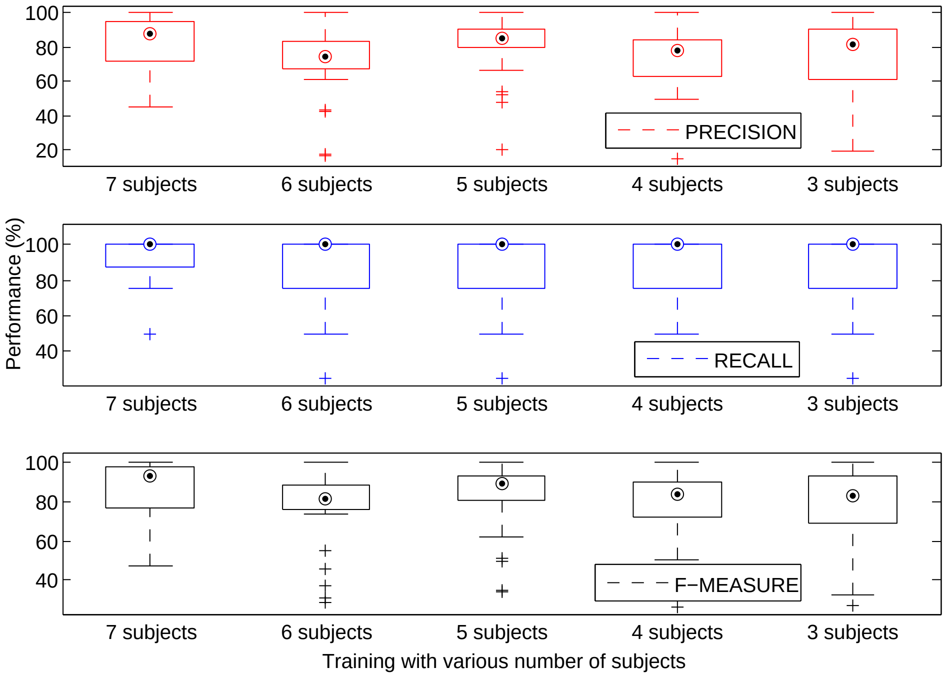

Figure 4.3: Results for DT based fall classification for training of various numbers of subjects.

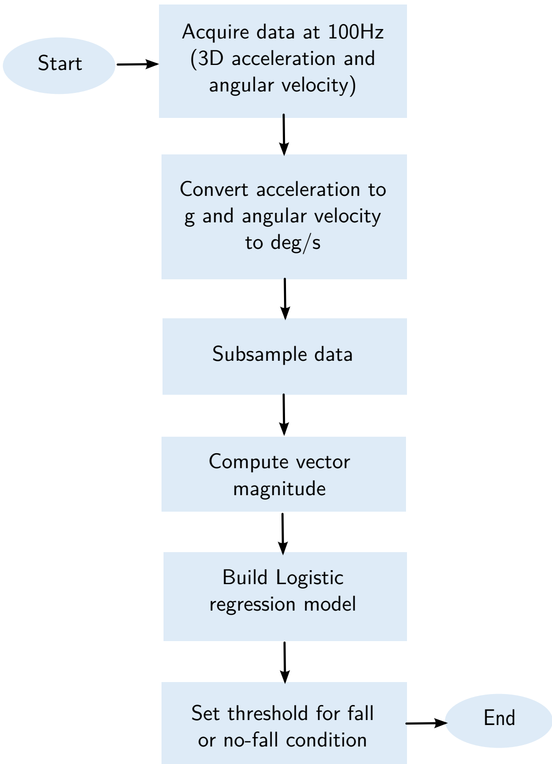

Figure 4.4: A flow chart showing an overview of the logistic regression based fall detection algorithm.

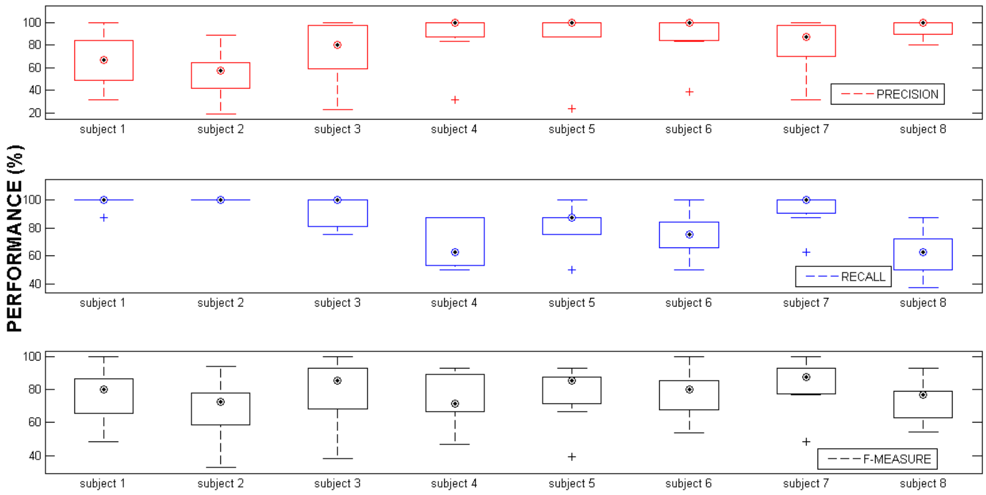

Figure 4.5: Results for testing the logistic regression algorithm via leave one subject out cross-validation.

Maximum likelihood estimation was used to estimate the regression coefficients (see Musicus and Lim [77]). Maximum likelihood selects the coefficients that make the observed outcomes most likely to occur by minimising the residual (the difference between the observed output value and the predicted value). For a normal distribution, the maximum likelihood can be described as:

$$f(X_1,\, X_2,\, ...X_n\,|\,\mu, \sigma) = \frac{(2\pi)^{-n/2}}{\sigma^n} exp\left[-\frac{\Sigma(x_i-\mu)^2}{2\sigma^2}\right] \tag{4.2}$$

Logistic regression is less computational intensive once the regression coefficients have been estimated. Therefore, it can be implemented in real time on an embedded device.

4.3.1 Implementation

Features The features used here were: i) x, y and z axes for acceleration and angular velocity and ii) VM for acceleration and angular velocity. These features were computed for both the chest and thigh sensor nodes.

Datasets Dataset 1 (D1) using Protocol 1 (8 subjects total, see Table 3.1).

As noted previously, the output of the logistic regression algorithm is a probability that varies between 0 and 1, and a probability values close to 0 means that falls are unlikely to have occurred and a probability value close to 1 means that falls are likely to have occurred. Thus, a threshold is required above which it is determined that a fall has occurred. If the threshold is set to be close to 1, few FPs will be recorded and some falls may be missed. However, if threshold level is close to 0, more of the falls will be detected with the penalty of a high level of FPs. In view of this, a threshold of 0.85 was set. This threshold level was determined by observing the output of the logistic regression across all gathered data.

4.3.2 Evaluation and results

Leave one subject out cross-validation was used to determine the accuracy of the logistic regression based algorithm. For each of the 8 subjects in turn, data from 1 subject was used for training and data from the remaining 7 subjects was used for testing. A summary of the results is shown in Figure 4.5. The algorithm gives an mean F-M between 68% and 82%. Furthermore, the algorithm gives, on average, an

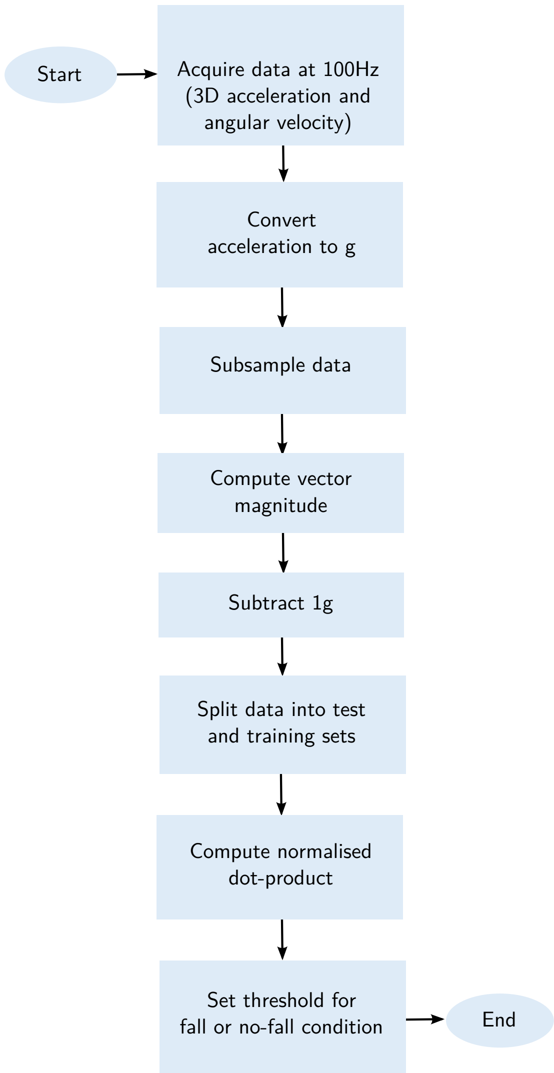

Figure 4.6: A flow chart showing a fall detection algorithm based on Dot-product

False Positive Rate (FPR) of 21% and an False Negative Rate (FNR) 16%. This results is below the baseline target of performance (F-M of 90%). The logistic regression algorithm is not suitable for fall detection given the selection criteria and the lower performance versus the decision tree based algorithm.

4.4 Dot-product based fall detection algorithm

This algorithm is based on the dot-product of two vectors (training and test data samples). The dot-product algorithm takes 2 input acceleration data vectors and computes the dot-product, returning a scalar value as the result. A overview of the dot-product algorithm is shown in Figure 4.6.

4.4.1 Implementation

Features The features used here were: VM for acceleration from the chest node.

Datasets Dataset 1 (D1) using Protocol 1 (8 subjects total, see Table 3.1).

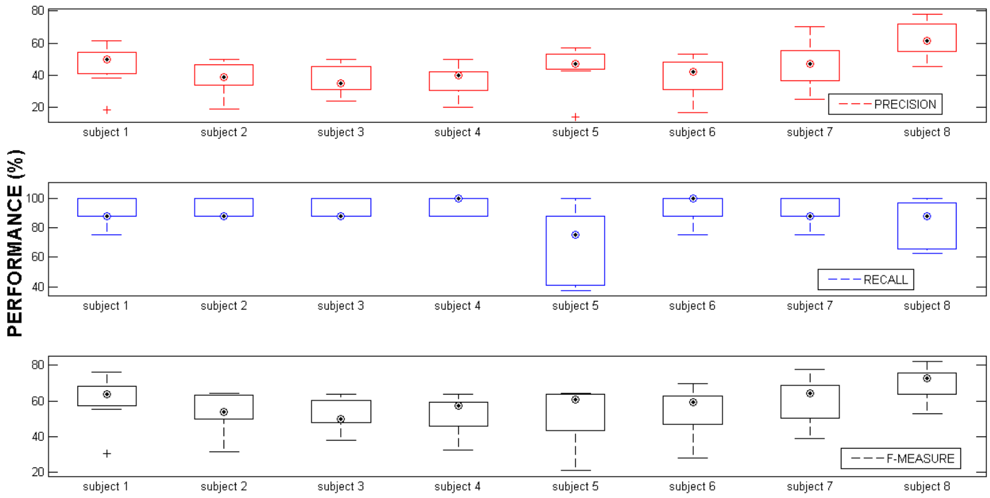

Figure 4.7: Results for testing the dot-product algorithm via leave one subject out cross-validation.

For static postures such as standing, the VM will have a 1 g offset due to the acceleration induced by gravity [13, 29]. Thus, 1 g was subtracted in order to eliminate this effect.

For the training set, sections of the data annotated as falls were identified and the point of impact for each fall (maximum peak of VM) was selected. This was performed for all falls and then a fall vector, which is defined as a 4 second window of acceleration data centred on the point of impact, was identified for all fall instances. An average fall vector for all fall vectors in the training set was then computed. In operation, a normalised dot-product between the training average fall vector and a sliding window over the test data is computed and compared to a threshold (set empirically based on results from across the datasets) to identify falls. The normalised dot-product approach is described in Equations 4.3 to 4.5. The training data average fall vector a is defined as

$$\vec{a} = (a_1, a_2, ..., a_n)^T \tag{4.3}$$

The test data vector b is defined as

$$\vec{b} = (b_1, b_2, ..., b_n)^T \tag{4.4}$$

The normalised dot-product c is therefore

$$c = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} \tag{4.5}$$

4.4.2 Evaluation and results

For each of the 8 subjects in turn, data from 1 subject was used from training and the remaining 7 subjects used for testing. A summary of the result of applying a dot-product approach on dataset D1 is given in Figure 4.7. The results of the evaluation show that the F-M varies between 52% and 70%. Overall, the algorithm records a higher recall compared to precision. The maximum and minimum recall is 95% and 68%, respectively, while for the precision is 62% and 37%. These results are relatively poor compared to the required baseline performance and also compared to the decision tree based approach.

Table 4.2: Summary of results from fall detection algorithms

Algorithm	Precision (%)	Recall (%)	F-Measure (%)
Decision tree	82 ±15	92 ±15	86 ±14
Logistic regression	79 ±24	93 ±14	82 ±17
Dot-product	62 ±11	82 ±16	70 ±10

Table 4.3: Wilcoxon ranked test for significance difference between Decision tree, Logistic regression, and Dot-product algorithms

	Dot-product	Logistic regression	Decision tree
Decision tree	**0.0078**	0.0781	-
Logistic regression	**0.0078**	-	-
Dot-product	-	-	-

4.5 Summary

This chapter establishes the potential of three fall detection algorithms. A summary comparing the results from the three fall detection algorithms implemented in this chapter is shown in Table 4.2. Though all algorithms provided F-M less than 90%, the C4.5 DT based algorithm delivered the best performance with a F-M of 86.4%. Furthermore, a Wilcoxon test was performed to determine if there is a significant difference in performance between the three algorithms discussed ($p < 0.05$). The results of the Wilcoxon test is as shown in Table 4.3. The test rejects the null hypothesis for the values in bold and thus the Dot-product algorithm is the worst of the three. The DT provides a slightly better performance than Logistic regression, but the Wilcoxon test does not prove this.

The main challenges in creating and evaluating fall detectors such as the ones proposed here are:

1. The data sampled during the majority of a fall is not unique to falls. For instance, sections of acceleration data annotated as falls are also similar to those annotated as ADL. Furthermore, transitions from one posture to another, in some instances, trigger high acceleration signals similar to falls. In order to improve performance, features must be found that can distinctly identify falls. Additionally, close examination of the stages inherent in a fall must be considered.

2. During evaluation, there is a need to determine an appropriate approach for how to count the number of TPs, FPs, True Negatives (TNs), and FNs. The performance of the tree-based algorithm was evaluated both at macro-event level and by comparing the annotation with the output of the algorithm. Both methods of evaluation introduce a level of ambiguity because sections of data classified as falls do not exactly match those annotated as falls. This implies that data classified as falls in some instances are not exactly the same as those annotated as falls. Ideally, each sample of data classified should be compared against their corresponding annotation. The next section discusses a logistic regression based fall detection algorithm.

The next chapter presents an in-depth discussion on the implementation, evaluation and the results of a micro-annotation machine learning based algorithm targeted at resolving the issues described here.

Chapter 5

Micro-annotation Based Machine Learning Algorithm

In the previous chapter, three algorithms were implemented and evaluated. This chapter describes a micro-annotation based machine learning fall detection algorithm and defines a design space for a decision tree based fall detection algorithm. The micro-annotation based algorithm computes features based on the history of the data of a fall and this history include the events that occurred before, during and after a fall. Thus, a fall is considered to consist of pre-impact, impact and post-impact stages. The evaluation of the micro-annotation based algorithm is done at micro-annotation level (sample by sample). The design space specifies the factors that impact on a classifier performance. Some of these factors include optimum features, sampling rate and training size.

The design space for a tree-based fall detection algorithm is large and there is no clear guidance in the literature on how to select the factors that impact on a classifier's performance. In this chapter, the section on micro-annotation fall detection investigates and identifies some of the major factors that impacts on a classifier performance. The factors investigated include: 1) subset of features necessary for optimum classifier performance, 2.) sensor placement, 3.) sampling rate and 4.) training size.

The contributions to knowledge brought in by this chapter are:

- A novel algorithm for fall detection based on micro-annotation.
- Selection of an optimum subset of features necessary for a machine learning based fall detection algorithm.
- A design space for a machine learning based fall detection algorithm.

The rest of this chapter is organised as follows: Section 5.1 describes a micro-annotation based machine learning algorithm. Section 5.2 presents the implementation of micro-annotation for fall data. Section 5.3 describes the feature extraction for a micro-annotation based machine learning fall detection algorithm. Section 5.4 presents the evaluation and results for the micro-annotation fall detection algorithm. Section 5.5 presents a design space for the micro-annotation based machine learning algorithm. Section 5.6 describes the performance comparison of the micro-annotation fall detection algorithm and Tynetec fall detector. Section 5.7 presents a summary of work in this chapter.

5.1 A micro-annotation based machine learning algorithm

This section describes a micro-annotation based machine learning algorithm developed for fall detection. This algorithm was developed based on three ideas: 1.) fall data must be annotated at a micro-level (that is, only one sample of data should be annotated as a fall for each fall event), 2.) features must be implemented based on fall history (pre-impact, impact and post-impact stages of a fall) and 3) algorithms must be evaluated at micro-level (only one sample of data should be classifies a fall for each fall event). The micro-annotation algorithm is based on C4.5 Decision Tree (DT) and consists of three stages:

Table 5.1: A list of constants used in Algorithm 5.1

Constant	Value
TIME__A	1s
TIME__B	2s
TIME__MAX1	1s
TIME__MAX2	10s
PRE-IMPACT__TIME	1s
IMPACT__TIME	6s
POST__IMPACT__TIME	9.5s
MAX__STATIC__ACTIVITY	1.6g
OVER__LAP	50%

1. *Micro-annotation of fall data* - Windows of data initially annotated as falls during data gathering (see Section 3.1.2) are re-annotated such that only one sample is annotated as a fall for each fall window.

2. Feature extraction - The features computed are based on the 3 fall stages discussed in Section 2.1.2.

3. Training a Decision Tree - The features extracted are used to train DT models. This stage produces DT models which are used to discriminate between falls and Activities of Daily Living (ADL). In this thesis, for training purpose, an ARFF format file (which consists of a list of input features and dataset) was created and supplied to Waikato Environment for Knowledge Analysis (WEKA) for training a decision tree.

Algorithm 5.1 and Figure 5.1 provide a description of the micro-annotation based algorithm. A list of constants used in the Algorithm 5.1 is shown in Table 5.1. The micro-annotation and feature extraction stages are novel aspects of this algorithm. A tree based algorithm makes a decision for each row of data independent of every other row and regardless of the order in which the data is presented. Hence, all the information required for a classifier to make decisions must be provided in that row. The approach used in this thesis is to compute features based on the history of fall data. That is, features are computed based on the events that occurred both before and after a fall, thus providing the history of information required by a classifier to correctly classify a fall. The history of fall data is segmented into pre-impact, impact and post-impact stages of a fall.

5.2 The implementation of micro-annotation approach for fall data

Micro-annotation is a term which describes how a segment of data annotated as a fall is re-annotated such that only one sample within that segment of data is annotated as a fall. This section gives the motivation for this approach and describes the process itself.

5.2.1 Challenges with window-based annotation approach

In order to highlight the importance of micro-annotation approach, the challenges with window-based annotation are first explained. Window-based annotation is when a segment of data is annotated as a fall for each fall event. For instance, during data gathering, each fall event was annotated as a window of data of approximately 3 seconds (see Figure 5.2). However, during evaluation of a DT based algorithm, the outputs of classifiers do not often align with segments of data annotated as falls even in cases where fall events are otherwise correctly classified. Figure 5.2 shows typical classifier output compared with the segment of data classified as a fall. The samples between 0.7 seconds and 3.0 seconds were annotated as a fall, but the classifier classified 1.6 seconds to 3.6 seconds as a fall. Thus, it becomes unclear whether to

Algorithm 5.1 Micro-annotation based machine learning algorithm training.

1. **x** ← obtain annotated sensor signal
2. **z** ← convert sensor signal to units (**x**)
   (**z** = (acceleration, angular_velocity, annotation))
3. **y** ← micro-annotate sensor signal (**z**) :
   for each segment of data annotated as a fall
   (a) identify the start and the end of the segment of data annotated as a fall
   (b) identify the sample of data with the maximum peak acceleration
   (c) annotate the sample of data which is TIME_A before the maximum peak a fall
4. **d** ← identify active-state (**z**) :
   (a) segment acceleration data into TIME_B interval
   (b) k ← identify the sample of data with the maximum peak acceleration
      i. if k > MAX_STATIC_ACTIVITY
      ii. label the sample of data which is TIME_A before the maximum peak as active-state
      iii. else label as not-active-state
5. (**i**, **j**) ← Compute tilt_angles (acceleration, angular_velocity) :
   (a) **i** ← compute tilt_angle from accel (acceleration)
   (b) **j** ← compute tilt_angle from angular_velocity (angular_velocity)
6. **c** ← combine accel and gyro tilt angles (acceleration, angular_velocity) :
   (a) (**i**, **j**) ← Compute tilt_angles (acceleration, angular_velocity)
   (b) fuse tilt angles from acceleration and angular velocity (**i**, **j**)
7. **t** ← compute absolute max for tilt_angle (**c**) :
   (compute absolute max at TIME_MAX1 and TIME_MAX2)
8. **f** ← compute feature components based on fall stages ( ) :
   (compute features at (PRE-IMPACT_TIME, IMPACT_TIME, POST_IMPACT_TIME) with (OVER_LAP) overlapping window)
   (a) f_c : (Mean ($\bar{x}_w$), Velocity (V), Energy (E), Variance (x_{var}), RMS ($V_{m_{rms}}$), EMA (s_t), SMA (γ))
9. **g** ← compute Min and Max acceleration ( ) :
   (compute features for Min and Max (TIME_A) interval with (OVER_LAP) overlapping window)
   (a) f_c : (Min ($V_{m_{min}}$) , Max ($V_{m_{max}}$))
10. m ← train tree (**d**, **c**, **f**, **g**, **t**, **y**)
    (m is the model tree generated after training)

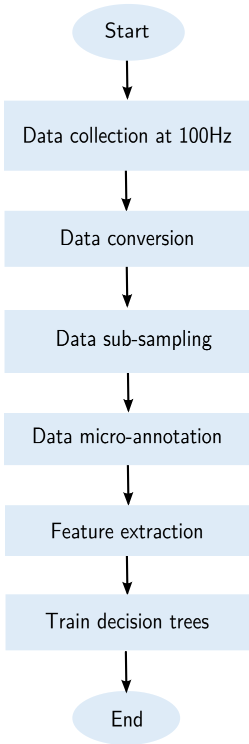

Figure 5.1: A flow chart showing the micro-annotation based algorithm development process.

consider the fall correctly classified or to consider from 0.7 seconds to 1.6 seconds as False Negatives (FNs) and 3.0 seconds to 3.6 seconds as False Positives (FPs).

In addition, in window-based annotation approach, segments of data classified as falls are different in length for each fall event. Thus, it is unclear how to determine the number of True Negatives (TNs). When the micro-annotation approach is used, each classification result can be compared to its corresponding annotation during evaluation, thus eliminating the ambiguity introduced by the window-based annotation approach.

5.2.2 Implementation of micro-annotation

A graphical illustration of micro-annotation of acceleration data is provided in Figure 5.3. The start of each fall is identified and re-annotated as a fall. The start of a fall is considered as 1 second before a subject makes impact with the floor. During a fall event, a short burst of high acceleration, which marks the point at which a subject makes contact with the floor, can be observed on the graph. During evaluation, the outputs of a classifier must match each sample of data annotated as a fall, for each sample to be considered correctly classified. Figure 5.4 shows a block description for the implementation of micro-annotation.

A summary of the process that the micro-annotation algorithm goes through is illustrated in Figures 5.5 - 5.7. The micro-annotation algorithm is implemented in two stages:

1. Micro-annotate data

2. Extract features

Micro-annotate data: The first stage is to re-annotate data previously annotated as falls during data collection such that only one sample of data within each segment is considered a fall. During data

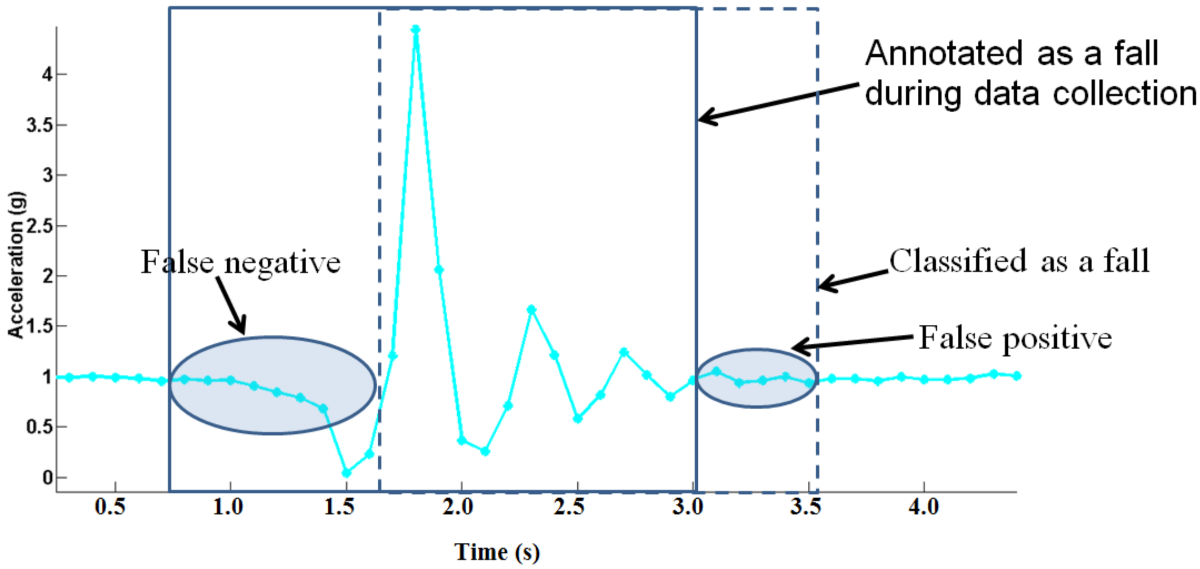

Figure 5.2: Problem with window based fall event annotation.

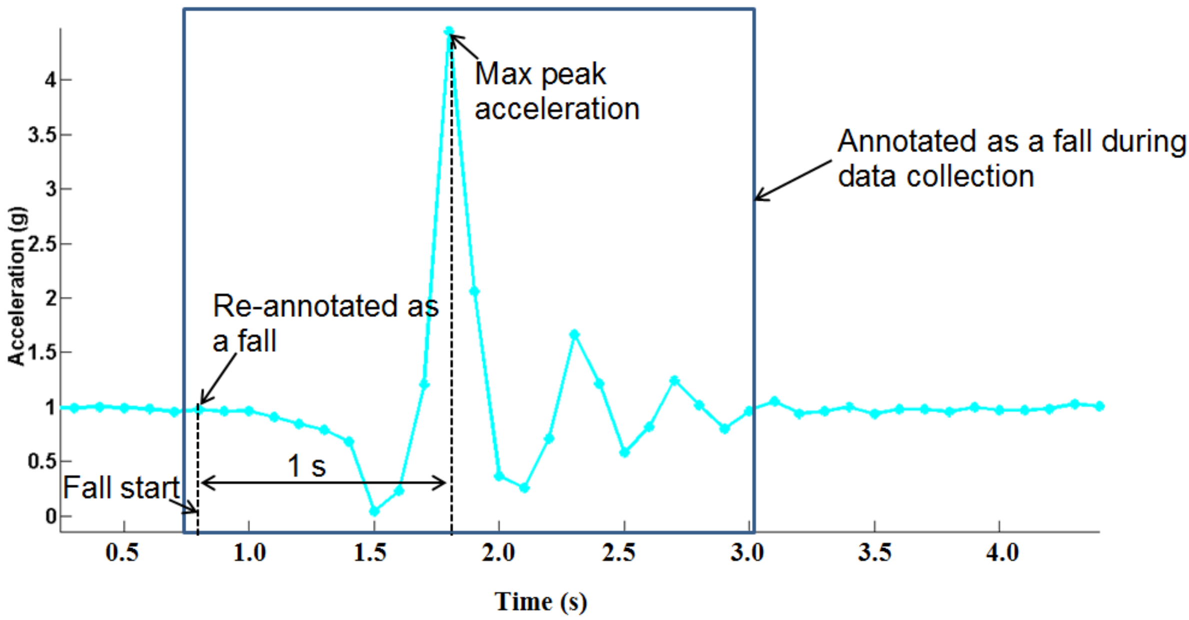

Figure 5.3: Micro-annotation based fall event annotation.

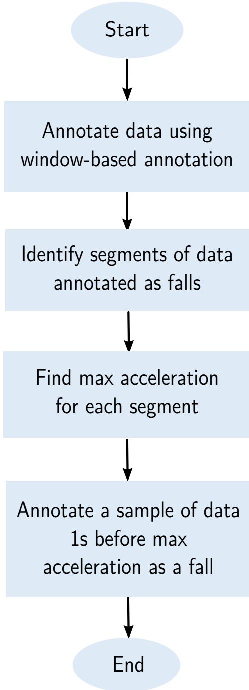

Figure 5.4: A flow chart showing the stages of micro-annotating fall data

collection, all samples from the time when a faller begins to fall until he makes contact with the ground and stays lying on the floor are annotated as fall samples. For example, one fall, shown in Figure 5.5, was annotated as a fall between times 26 seconds and 32 seconds. In order to micro-annotate the data, only one sample within that segment of data is re-annotated as a fall (see Figure 5.6). The micro-annotation algorithm requires that only one sample is classified as a fall per fall instance. The sample chosen is one that is one second prior to the peak acceleration during the fall.

Extract features: The second stage of micro-annotation is to extract features. The feature extraction process involves determining if a subject is active or not (active-state) and extracting features based on the three fall stages. Active-states are defined as activities that trigger acceleration signals greater than 1.6g. Samples of data greater than 1.6g threshold are labelled as 1 (active-state) (see Figure 5.7). The rest of the features extracted are based on the three fall stages (see Section 5.3) and are computed over a moving window of data of 12 seconds. The features include: the Tilt-angle, Exponential Moving Average, Root Mean Square, Signal Magnitude Area, Min, Max, Mean, Velocity, Energy and Variance.

5.3 Feature extraction

This section describes the features extracted for a micro-annotation based machine learning algorithm. As noted previously in Section 5.1, the micro-annotation based algorithm extracts features based on fall stages.

Feature extraction is discussed in Section 5.3.1 (Feature components) and 5.3.2 (Feature implementation for the three stages of falls). Section 5.3.1 specifies a set of statistical computations implemented for each fall stage, while Section 5.3.2 describes how these features were used as input attributes for the classification algorithm.

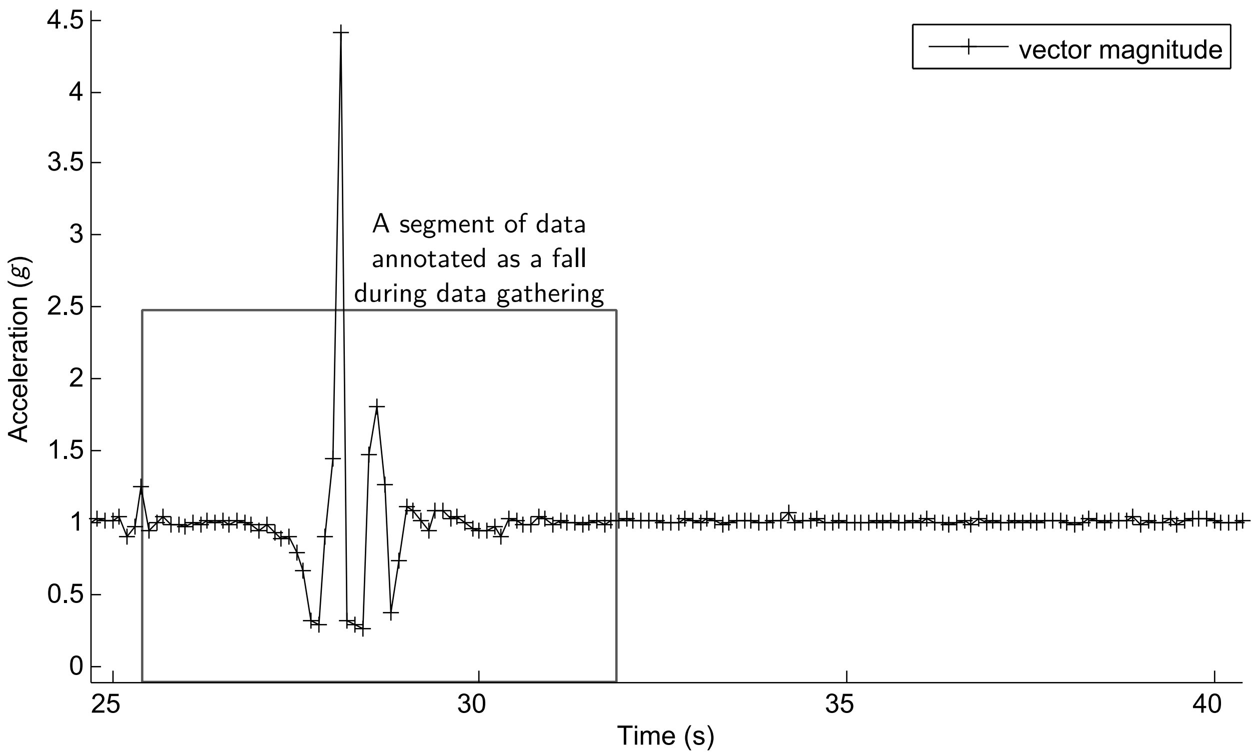

Figure 5.5: Conversion from window-based annotation to micro-annotation

5.3.1 Feature components

The feature components extracted are based the on the computed Vector Magnitude (V_m). The feature components are as follows and are summarised in Figure 5.8.

Active-state: Falls are events (sudden motion that occurs for a short period of time) and often result in acceleration signals with higher amplitude than ADL. Acceleration signal when a subject is sedentary is approximately $1g$ and rises above $1.6g$ when active [1, 24]. By identifying acceleration signals above $1.6g$, data samples which contain fall information and other events can be separated from sedentary ADL. Therefore, *active-state* monitors subject's acceleration level to determine if they are in an active state or sedentary. This monitoring is performed over 2 second periods because falls normally occur over 3 seconds [22].

Min ($V_{m_{min}}$)**:** The minimum value of a Vector Magnitude (VM) ($V_{m_{min}}$) over a window of 1 second was used to identify the pre-impact stage of a fall. The Vector Magnitude tends toward zero at the pre-impact stage [49].

Max ($V_{m_{max}}$)**:** The maximum value of the VM ($V_{m_{max}}$) over the next 1 second window of data with 50% overlap was used to derive the impact stage. The time window for the pre-impact and impact takes into consideration the logical transition of a faller from when a fall starts till an impact with the floor occurs [49].

Mean ($\bar{x}_w$)**:** The mean acceleration is higher, for when a faller begins to fall, till an impact is made with the ground, than when the faller is in a static postures. A similar magnitude of acceleration can be observed during a dynamic activity. The mean ($\bar{x}_w$) of V_m from the start of a fall for the next 1 second, 6 second and 9.5 second were calculated with 50% overlap. The mean computed over

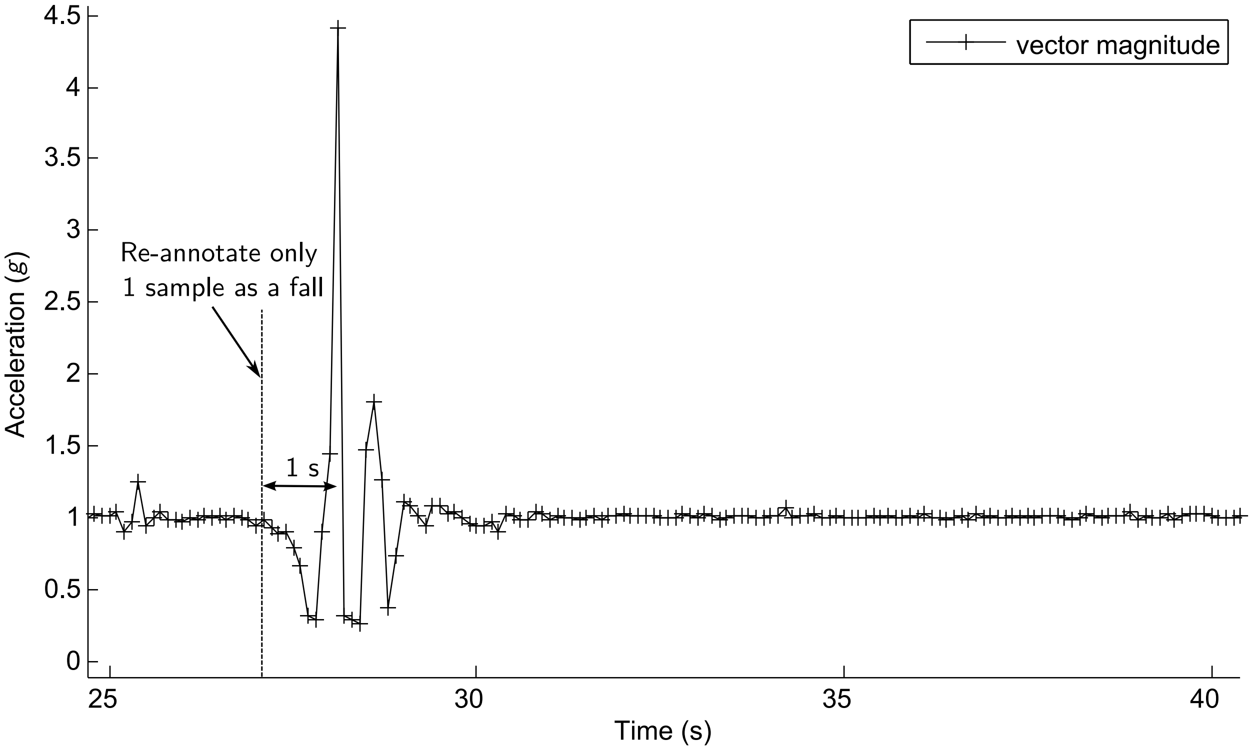

Figure 5.6: One sample of data re-annotated as a fall

these time segments allow for the acceleration of subjects at the beginning of a fall, during, and after a fall to be captured [36]. Mean is calculated as:

$$\bar{x}_w = \frac{1}{n} \sum_{k=t-n+1}^{t} V_{m_k} \tag{5.1}$$

Velocity (V)**:** The velocity of V_m was computed. Similar to the mean of acceleration, the overall velocity of the body tends to be higher during a fall than during static activities [13]. Velocity is calculated as:

$$V = \int (V_m) dt \tag{5.2}$$

Energy (E)**:** The energy expenditure was computed for pre-impact, impact and post-impact stage [34].

$$E = \int (a_x^2) dt + \int (a_y^2) dt + \int (a_z^2) dt \tag{5.3}$$

Variance (x_{var}): The windowed variance was computed for pre-impact, impact and post-impact stage [17].

$$x_{var} = \frac{1}{n} \sum_{k=t-n+1}^{t} (V_{m_k} - \overline{V}_m) \tag{5.4}$$

where $\overline{V}_m$ is the mean Vector Magnitude, $t = 1..n$

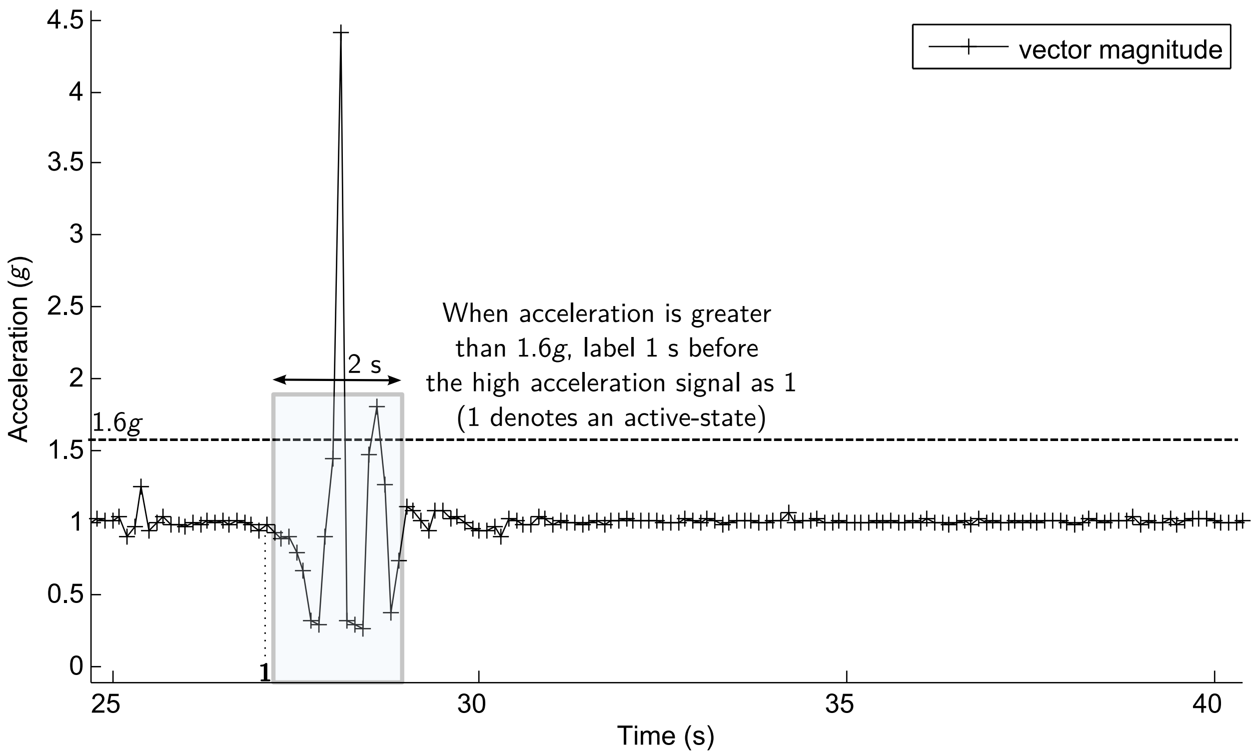

Figure 5.7: Identification of active-state

RMS ($V_{m_{rms}}$)**:** The Root Mean Square (RMS) is the magnitude of an oscillating signal. The RMS is useful in capturing the magnitude of acceleration signal during activities such as walking and ascending and descending a staircase [14, 36].

$$V_{m_{rms}} = \sqrt{\frac{1}{n}\left(V_{m_{t_1}}^2 + V_{m_{t_2}}^2 + ... + V_{m_{t_n}}^2\right)} \tag{5.5}$$

EMA (s_t)**:** The Exponential Moving Average (EMA) is similar to the moving average but applies an exponentially decreasing weight to past observations [17].

$$s_t = \alpha V_{m_t} + (1-\alpha)s_{t-1} \tag{5.6}$$

SMA (γ)**:** The Signal Magnitude Area (SMA) is the sum of the area of each axis of the acceleration data [51, 126].

$$\gamma = \frac{1}{t}(\int_0^t |x|dt + \int_0^t |y|dt + \int_0^t |z|dt) \tag{5.7}$$

Tilt angle (Forward-backward, lateral tilt angle): From the start of a fall (pre-impact) till the point of rest, a change in orientation or change in tilt angle of a subject can be observed. Change in orientation is as a result of subject's change in posture from either upright or sitting position to lying or semi-lying position [20].

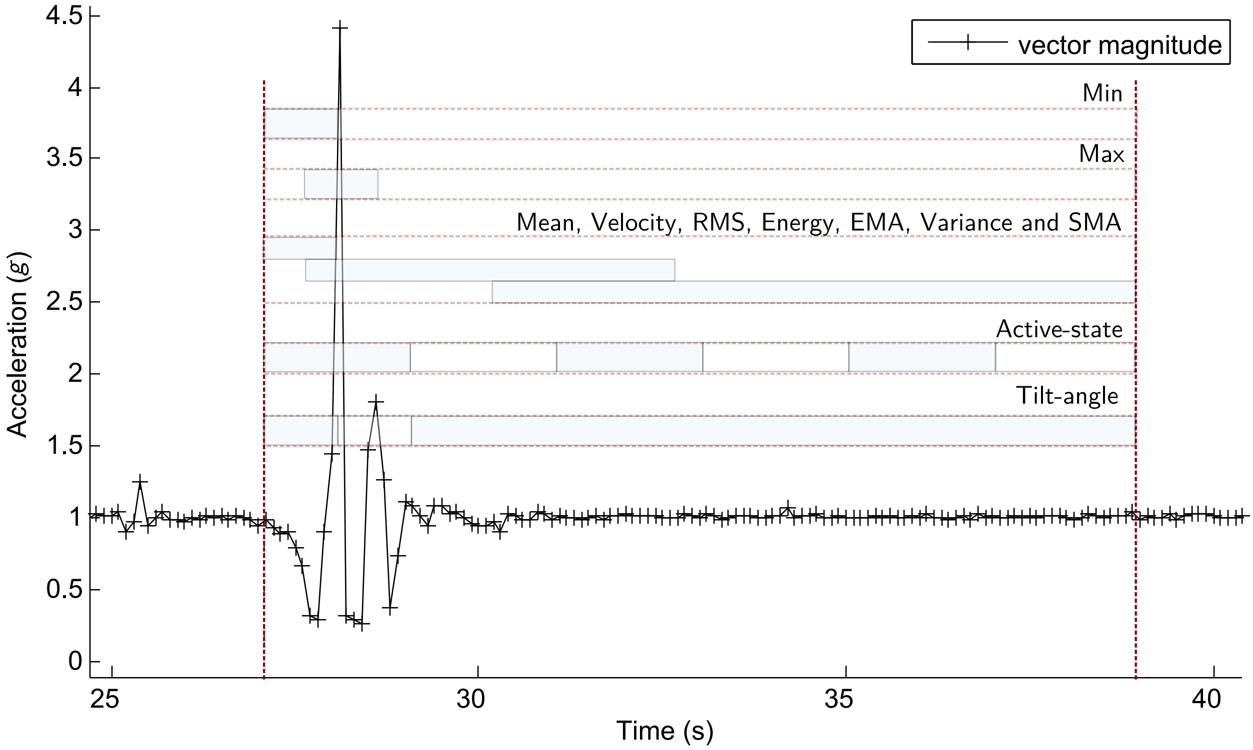

Figure 5.8: A timeline showing the features extracted for the micro-annotation fall detection algorithm

- Tilt angle accelerometer (θ_{accel})

$$\theta_{accel=} \arctan(\frac{a_z^2}{\sqrt{(a_x^2 + a_y^2)}}) \tag{5.8}$$

- Tilt angle Gyro (θ_{gyro})

$$\theta_{gyro} = \int (\omega)dt \tag{5.9}$$

where ω is the angular velocity

The tilt angle of a subject from the start of a fall for the next 12 seconds was observed for both the y and z axes of the shimmer sensor node (sagittal and coronal planes). The tilt angle over 12 seconds was split into 3 segments (absolute maximum angle of over 1 second, over the next 1 seconds and over the next 10 seconds without overlapping). By splitting the tilt angle into 3 segments, the orientation of a faller can be observed separately at the start and end of a fall, because fallers experience a change in posture during falls. The tilt angle was derived by combining the calculated tilt angles from both an accelerometer and a gyroscope using a Kalman filter. Before deriving tilt angles from the angular velocity, it was first high-pass filtered using a second order Butterworth filter with a cut-off frequency of 0.05 Hz. Filtering in this instance reduces drift that can be observed during the integration of the angular velocity. By combining the tilt angle from accelerometer and gyroscope, a more accurate tilt angle was derived. If accelerometer data alone is used to compute the tilt angle, the tilt angle can be less accurate during a dynamic event such as a fall because an accelerometer measures the acceleration of the body it is strapped to. On the other hand, the output of a gyroscope drifts during integration over time. A Kalman filter was used to overcome the limitations of the accelerometer and gyroscope by combining both tilt angles and predicting the best guess for the tilt angle [52]. A summary of the Kalman filter is shown in Equations 5.10–5.16.

- Tilt angle Kalman filter (θ_t) : in this application, the Kalman filter estimates the state (x_t) of a discrete time controlled process that is governed by the linear stochastic (random variable) difference equation:

$$\begin{aligned} x_t &= Ax_{t-1} + w_{t-1} \quad (5.10) \\ z_t &= Hx_t + v_t \quad (5.11) \end{aligned}$$

where x is the state estimate, z is the measurement, w is the process noise and v is the measurement noise. A and H are the state transition and measurement matrices, respectively. The tilt angle using Kalman filter is given by:

$$\begin{aligned} \hat{x}_t^{'} &= A\hat{x}_{t-1} \quad (5.12) \\ p_t^{'} &= Ap_{t-1}A^T + Q \quad (5.13) \\ K_t &= p_t^{'}H^T(Hp_t^{'}H^T + R)^{-1} \quad (5.14) \\ \hat{x}_t &= \hat{x}_t^{'} + K_t(z_t - H\hat{x}_t^{'}) \quad (5.15) \\ p_t &= (I - K_tH)p_t^{'} \quad (5.16) \end{aligned}$$

where

$\hat{x}^{'}$ - prior state estimate

$\hat{x}$ - predicted state estimate

K - Kalman gain

p - measurement posteriori error covariance

$p^{'}$ - updated priori error covariance

Q - process noise covariance

R - measurement noise covariance

I - identity matrix

$\hat{x}_{t-1}$ and z_t are θ_{accel} and θ_{gyro}, respectively, and $\hat{x}_t$ is the estimated tilt angle θ_t.

5.3.2 Feature implementation for the three stages of falls

This section describes how each feature component was implemented. Figure 5.10 shows the three stages of falls (pre-impact, impact and post-impact) around which each feature component was implemented.

For both training and testing, the feature components were computed over a window of 12 seconds of data. Features were computed for pre-impact, impact and post-impact stages of a fall. The Min of Vector Magnitude ($V_{m_{min}}$) was computed for the first 1 second. This Min depicts the time over which a faller experiences a free-fall before making an impact with the floor. The Max of Vector Magnitude ($V_{m_{max}}$) was calculated for the next 1 second, overlapping by 50% with $V_{m_{min}}$in order to detect when a faller makes an impact with the ground. Falls are events with higher acceleration amplitudes than static activities; therefore, the *active-state* was computed over every 2 seconds window of data without over-lapping in order to discriminate between a state of sedentary and state of activity. Figure 5.9 shows a block description for *active-state.*

When a fall occurs, the tilt angle of a faller changes from initial body orientation at the start of a fall until the faller comes to rest on the floor. The absolute Max tilt angle for the first 1 second was

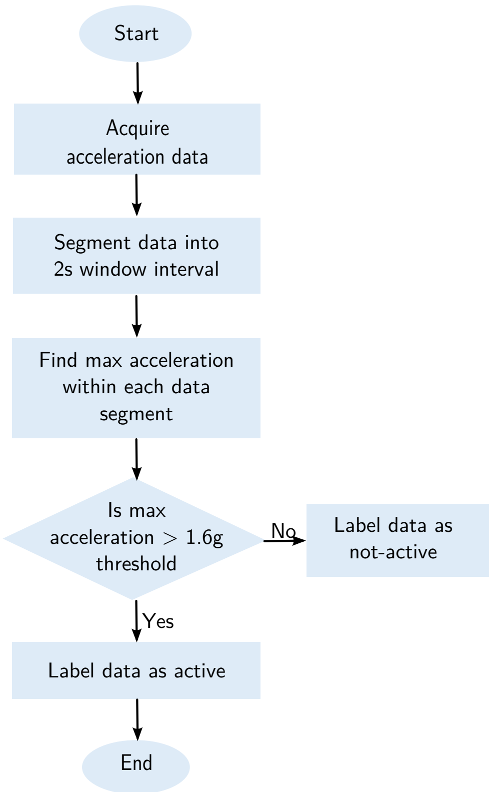

Figure 5.9: A flow chart showing the *active-state* decision process

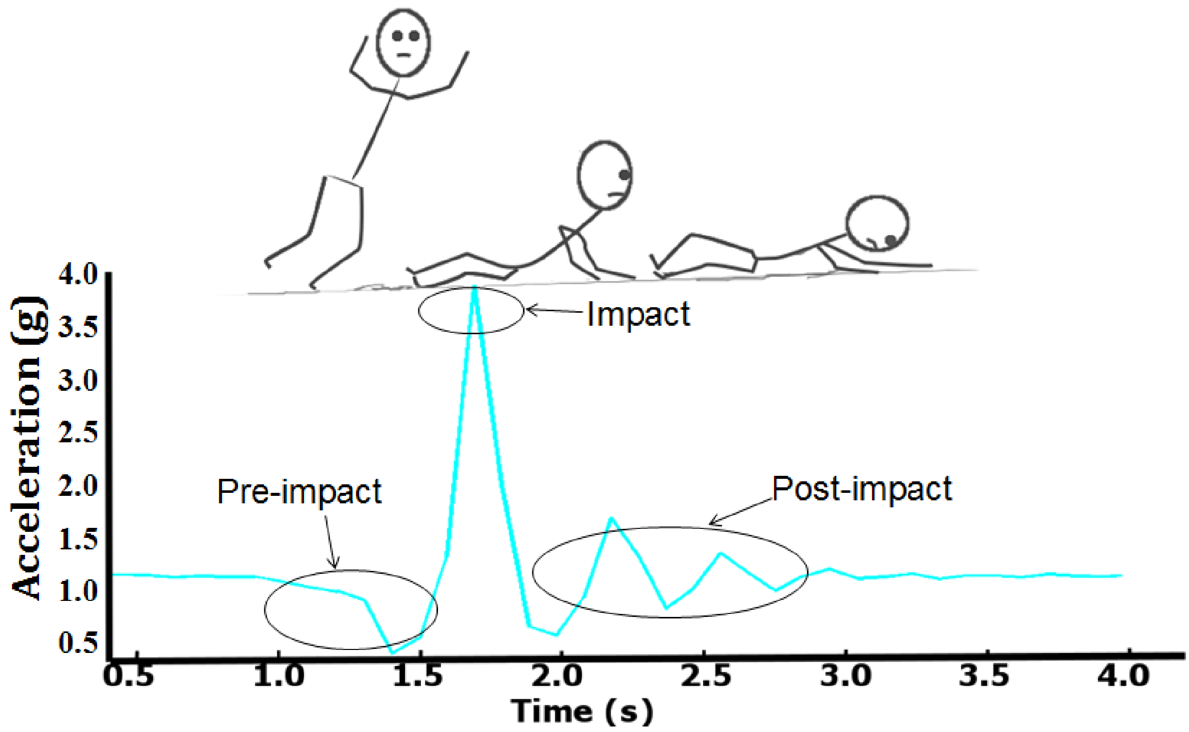

Figure 5.10: The three fall stages.

calculated. This tilt angle provides information regarding the tilt angle of the body at the start of a fall. Followed by the absolute Max tilt angle for the next 1 second. This stage is considered as a transition from the start to the end of a fall. Thus this tilt angle was not used as a feature. The next 10 seconds of absolute Max of the tilt angle is then computed to determine the fallers inclination after a fall. The third tilt is useful for distinguishing between falls and other activities or events such as near-falls in which the subject momentarily bends their trunk region during a loss of balance.

The Mean ($\bar{x}_w$) , Velocity (V), Energy (E), Variance (x_{var}), RMS ($V_{m_{rms}}$) , EMA (s_t) and SMA (γ) were computed for 3 segments of data samples. The times for which these feature components were computed are, the first 1 second, the next 6 seconds and next 9.5 seconds with 50% overlapping window of data. Computing these features over these segments of data samples ensures that the different stages of falls are captured.

Table 5.2 gives a summary of the feature vector and which feature components were calculated for each fall stage.

5.4 Evaluation of the micro-annotation based machine learning algorithm

This section evaluates the micro-annotation based machine learning fall detection algorithm. Two evaluations were conducted: 1.) evaluation of micro-annotation algorithm based on all features in a feature vector and 2.) based on each feature component. The evaluations use dataset 2 (Table 3.1, Protocol 2) and leave one subject out cross validation was used.

Table 5.2: Features extracted for each fall stage.

Pre-impact stage	**Impact stage**	**Post-impact stage**
Variance (x_{var})	Variance (x_{var})	Variance (x_{var})
SMA (γ)	SMA (γ)	SMA (γ)
RMS ($V_{m_{rms}}$)	RMS ($V_{m_{rms}}$)	RMS ($V_{m_{rms}}$)
EMA (s_t)	EMA (s_t)	EMA (s_t)
Mean ($\bar{x}_w$)	Mean ($\bar{x}_w$)	Mean ($\bar{x}_w$)
Velocity (V)	Velocity (V)	Velocity (V)
Energy (E)	Energy (E)	Energy (E)
Min ($V_{m_{min}}$)	Max ($V_{m_{max}}$)	Forward-backward tilt angle
Forward-backward tilt angle	Active-state	Lateral tilt angle
Lateral tilt angle		

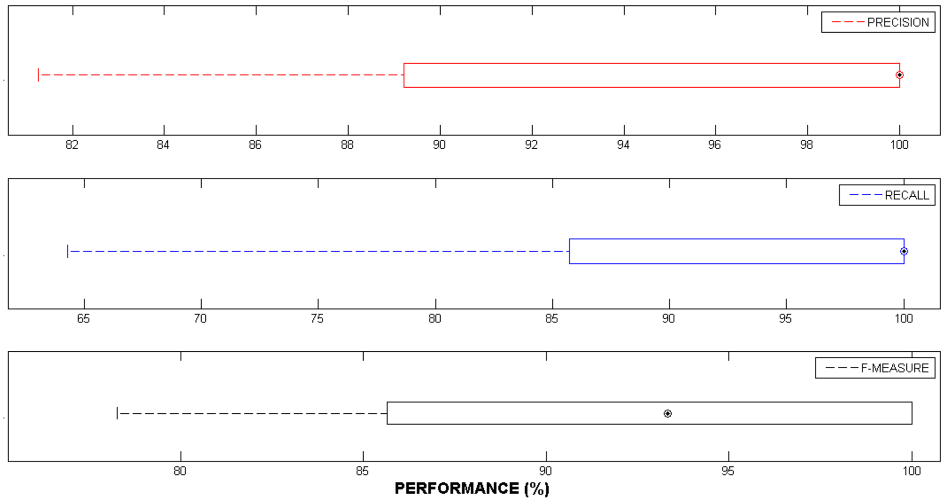

Figure 5.11: Leave one subject out cross validation based on all feature components

5.4.1 Evaluation based on all feature components

A summary of the results is shown in Figure 5.11. The result presents an F-Measure (F-M) with a median of 93% and mean of 91%. The micro-annotation fall detection algorithm therefore meets the performance criteria established in Section 2.8 (F-M > 90%). In order to determine which features are redundant, the next section investigates how the algorithm performs when trained with each individual feature component at a time.

5.4.2 Evaluation based on each feature component

The 10 feature components implemented in this thesis were described in Section 5.3. An investigation was conducted to determine how each feature component performs when used to train a decision tree. This evaluation was intended to provide an understanding on how each feature component impacts on the performance of a classifier. Each tree was trained by using each feature component based on leave one subject out cross validation for 32 subjects.

A summary of the results of evaluation is shown in Figure 5.12. Results show that “Mean” presents the best performance with F-Measure upper quartile and lower quartile of 96% and 89%, respectively. Min gave the lowest performance with the F-Measure upper quartile and lower quartile being 90% and 62%,

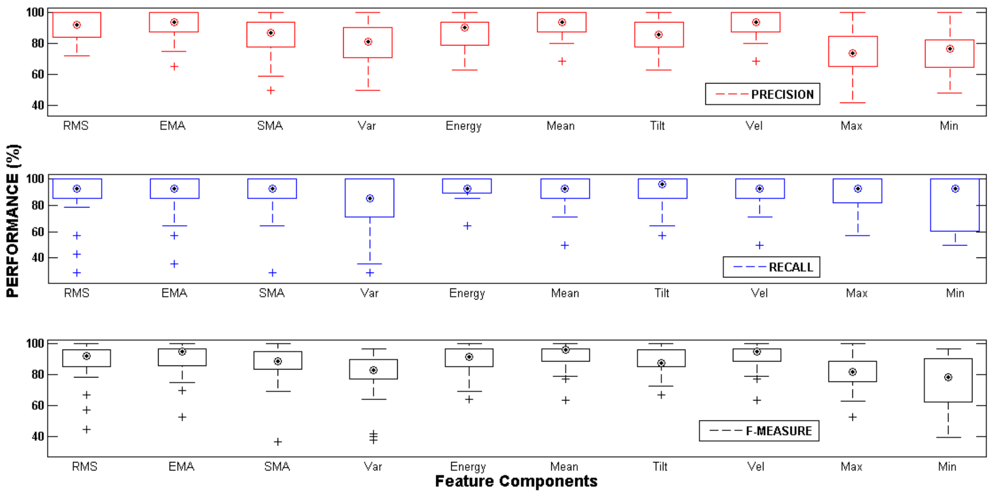

Figure 5.12: Evaluation results for each feature component

respectively. However, because this analysis was conducted based on an individual feature component alone, it does not show how a combination of the feature components impact on performance and it is also possible that some feature components provide the same level of information for the classifier. A feature selection approach that takes into consideration the influence of each feature on the whole feature set is discussed in the next section.

5.5 Design space for the micro-annotation based machine learning algorithm

The section discusses the factors that can impact on the performance of a machine learning fall detection algorithm. A number of research questions were formulated to guide the discussion on the design space for a tree based fall detection algorithm.

5.5.1 Research questions

1. What subset of features are essential to accurately detect falls?
2. Will placing a sensor on chest allow for better performance than placing it on the thigh?
3. What is the minimum sampling frequency necessary for the micro-annotation based fall detection?
4. What is the minimum number of subjects required to train a tree based algorithm?

Answers to research questions are presented next.

5.5.2 Feature selection

What subset of features are essential to accurately detect falls?

Identifying a subset of features from a feature vector is essential in order to eliminate redundant features, thus improving performance. Feature selection identifies and removes those features that provide little or no information to a tree model, by computing the information gain for each feature and evaluating its impact when combined with other features in the feature vector [45, 56].

Table 5.3: Subset of features selected

Pre-impact stage	Impact stage	Post-impact stage
Variance (x_{var})	Variance (x_{var})	Variance (x_{var})
SMA (γ)	RMS ($V_{m_{rms}}$)	Forward-backward tilt angle
EMA (s_t)	EMA (s_t)	
Min ($V_{m_{min}}$)	Active-state	
Energy (E)	Energy (E)	
	Max ($V_{m_{max}}$)	

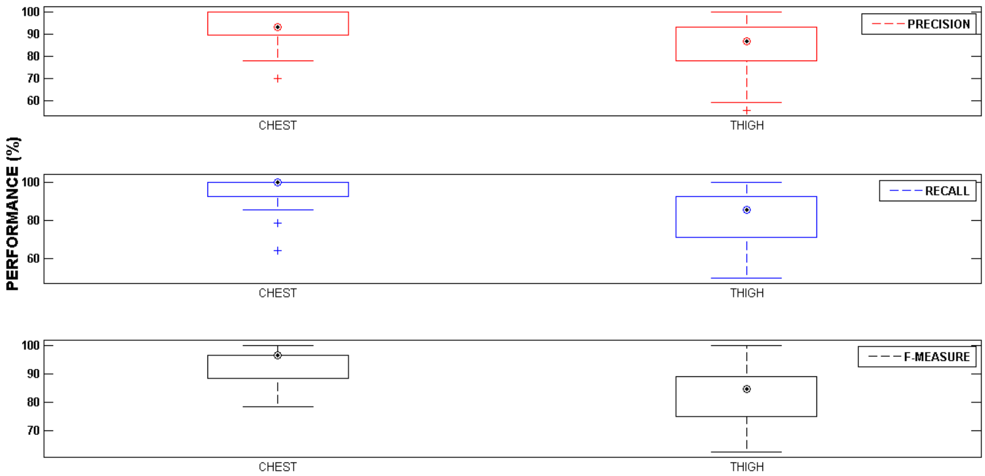

Figure 5.13: Comparison between chest and thigh sensor nodes

A feature selection method, known as the "Wrapper method", was used for feature selection. The Wrapper method is provided as part of WEKA tool kit. The Wrapper method uses a subset evaluator to create all possible feature subsets from a feature vector (see Table 5.2) and it uses a classifier (C4.5 decision tree) to determine the performance of each subset. The subset of features that gives the best performance is then identified.

The feature vector in Table 5.2 on page 62 is composed of 28 features and the Wrapper feature selection method was implemented to select the optimum features required for a machine learning based fall detection algorithm. The Wrapper, feature selection method selected 13 features (optimum features, see Table 5.3) out of the complete set of 28 features.

5.5.3 Sensor placement

Will placing a sensor on chest allow for better performance than on the thigh?

In order to minimise discomfort, wearers of fall detectors are often only instrumented with one sensor node [29, 122, 125]. A review of the literature (Section 2.7.2, Page 21) established that the chest is the best location to place a fall detector. This section further compares the performance between the chest and thigh sensor nodes. This comparison verifies whether the chest sensor node provides a higher fall detection performance than the thigh sensor node. A leave one subject out cross validation was performed for both the chest and thigh sensor nodes. A summary of the results are shown in Figure 5.13. The results show that chest sensor had a mean F-M of 93% and thigh sensor had a mean of 83%. Thus, it can be concluded from this analysis that the chest sensor node provides a higher classification performance than the thigh sensor node. The difference in performance between the chest and thigh sensor node is due to

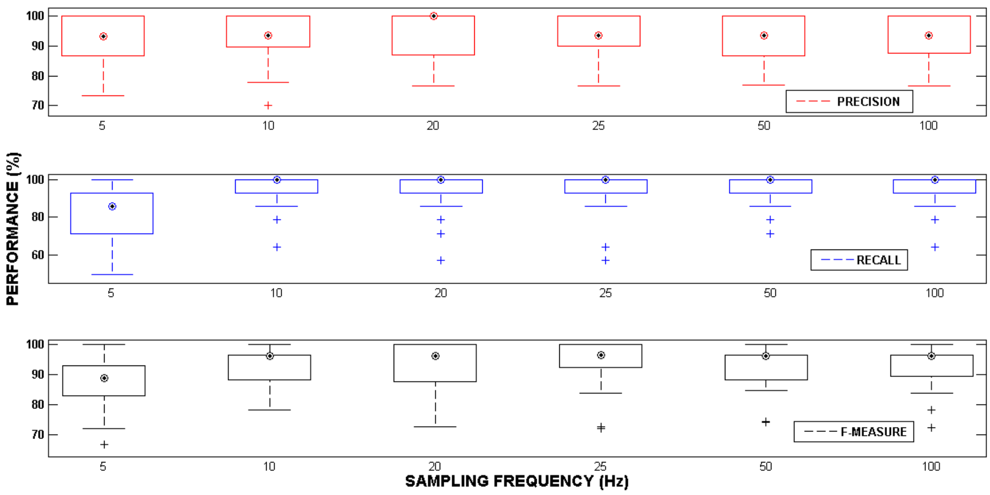

Figure 5.14: Leave one subject out cross-validation sampling frequencies 5 - 100 Hz

non-linearity and high variation in acceleration levels in the thigh region during normal motion [135].

5.5.4 Minimum sampling frequency

What is the minimum sampling frequency necessary for micro-annotation based fall detection?

Wearable fall detectors are based on small standalone processor systems, which have resource constraints such as processing power and battery life. As such, sampling at high frequencies will require more processing power and impact on the battery life. Thus, it is necessary that a fall detector samples at a frequency as low as possible whilst maintaining good performance (F-M over 90%). With a consideration to resource constraints, an evaluation was performed to determine the lowest frequency at which a micro-annotation based algorithm will provide a detection rate above F-M 90% (90% was selected based on the state of the art (see Section 2.8)). A leave one subject out cross validation was performed at 5, 10, 20, 25, 50 and 100 Hz. As mentioned in Chapter 3, data gathering was performed at 100 Hz, and during data analysis, data was down-sampled. The performance at various frequencies is shown in Figure 5.14. The figure shows that sampling at 25 Hz provides the best performance for mean precision (93.9%), recall (94.9%) and F-M (94.0%). As the frequency increases to 50 Hz and 100 Hz, the median, upper and lower quartile dropped by 1%. Similarly, as the sampling frequency drops from 20 Hz to 5 Hz, performance can be seen to drop. A drop in performance can be observed from 10 Hz to 5 Hz. Overall, the result shows that sampling at 10 Hz gives a precision, recall and F-M above 90%, while at 5 Hz performance drops below 90%. The performance gradually decreases with increase in sampling frequency from 25 Hz to 100 Hz.

Further analysis was performed to determine if there is a significant difference (p-value < 0.0001) in performance between each of the sampling frequencies. A Wilcoxon signed-rank test (an alternative to t-test for non-normal distribution) was performed to determine if there is a significant difference in performance at various sampling frequencies (5, 10, 20, 25, 50 and 100 Hz). The Wilcoxon signed-rank test tests the null hypothesis that states that there is no significant difference in the mean of the results for each sampling frequency. A summary of the performance is presented in Table 5.4. The test rejects the null hypothesis for the values in bold. These correspond to a 95% confidence level that the null hypothesis, that the two populations have the same mean, can be rejected. The table shows that there is a significant difference between 5 Hz and the rest of the frequencies. In addition, there is a significant difference between 25 Hz and 50 Hz. From these results, it can be concluded that there is no significant

Table 5.4: Analysis of Wilcoxon test for different frequencies showing the p-value (with feature selection)

Sampling freq. (Hz)	5	10	20	25	50
5	-	-	-	-	-
10	$\mathbf{3.39 \times 10^{-5}}$	-	-	-	-
20	$\mathbf{8.90 \times 10^{-5}}$	0.97	-	-	-
25	$\mathbf{4.57 \times 10^{-5}}$	0.55	0.49	-	-
50	$\mathbf{5.70 \times 10^{-3}}$	0.17	0.16	$\mathbf{9.30 \times 10^{-3}}$	-
100	$\mathbf{1.70 \times 10^{-3}}$	0.83	0.62	0.07	0.51

difference between the mean at 10, 20, 25, 50 and 100 Hz.
From Figure 5.14 and Table 5.4, the results show that sampling at 10 Hz is sufficient for fall detection. Sampling below 10 Hz will impact on performance and increasing frequencies from 10 Hz to 100 Hz does not result in a significant improvement in performance of a fall detection algorithm. As noted previously, sampling at a frequency as low as 10 Hz is desirable in order to reduce hardware resource requirements and improve battery life.

5.5.5 Minimum number of subjects required for training

What is the minimum number of subjects required to train a tree based algorithm?

In developing a machine learning based fall detector, it is essential to know the minimum number of subjects necessary to train a classifier. Training with more subjects than needed will increase demand on processing power and increase time spent on training a classifier. On the other hand, training with fewer subjects will impact negatively on the performance of a classifier. An analysis was performed to determine the minimum number of subjects necessary to train a classifier. The analysis in this section performs a leave n subjects out cross validation ($for\ n = 1 : 28$). A total of 32 subjects from dataset 2 (Protocol 2, see Table 3.1) were used in this analysis. For leave n subjects out cross validation, n subjects were selected at random for training and the remaining subjects $(32 - n)$ were used for testing.

A summary of the results is shown in Figure 5.15 and Table 5.5. From the graphs, the mean precision varies between 94.5% and 93% for leave 1 to leave 24 subjects out. For leave 25 subjects out, performance dropped to 92% and continues to drop further to 89% for leave 28 subjects out cross validation. From this results, it can be concluded that training with less than 6 subjects will affect performance negatively (F-M less than 91%) and training with more than 12 subjects is not likely to improve performance. Thus, training with at least 10 subjects is recommended for a tree based algorithm development.

5.6 Performance comparison of the micro-annotation fall detection algorithm and Tynetec fall detector

In previous sections, the micro-annotation based machine learning algorithm was developed and evaluated. In addition, a Wrapper feature selection algorithm was implemented and the design space for a machine learning fall detection algorithm was specified. This section focuses on:

1. The performance of the micro-annotation fall detection algorithm based on the optimum features selected (13 feature subset) versus the performance of the same algorithm with all 28 features in the feature vector.
2. The performance of the micro-annotation based fall detection algorithm versus the performance of a commercial fall detector.

Thus, this section highlights the advantages of the micro-annotation fall detection algorithm based on the 13 feature subset over using all features in the feature vector. Also, it describes the improvements

Table 5.5: Mean values for Precision, Recall and F-Measure for Leave n subjects out cross validation (*for* $n = 1 : 28$)

Leave n subjects out cross validation (*for* $n = 1 : 28$)	PR (%)	RC (%)	F-M (%)
1	93 ±8	94 ±10	93 ±7
2	94 ±7	95 ±8	94 ±6
3	94 ±7	95 ±9	94 ±6
4	94 ±7	95 ±9	94 ±7
5	94 ±7	95 ±8	94 ±7
6	93 ±7	96 ±8	94 ±6
7	93 ±7	95 ±8	94 ±6
8	93 ±7	95 ±8	94 ±6
9	93 ±7	95 ±9	94 ±6
10	94 ±6	94 ±9	94 ±6
11	94 ±7	94 ±9	94 ±6
12	93 ±7	96 ±9	93 ±6
13	94 ±7	94 ±9	94 ±6
14	93 ±7	95 ±9	93 ±6
15	92 ±8	95 ±8	93 ±6
16	92 ±8	95 ±8	93 ±6
17	95 ±7	95 ±9	94 ±7
18	95 ±7	95 ±9	95 ±6
19	93 ±8	96 ±7	94 ±6
20	93 ±8	95 ±9	94 ±7
21	94 ±8	94 ±8	94±6
22	95 ±7	94 ±9	94 ±6
23	93 ±7	95 ±8	94 ±6
24	94 ±7	95 ±8	94 ±6
25	90 ±10	95 ±8	92 ±7
26	91 ±10	94 ±9	92 ±8
27	88 ±11	94 ±9	91 ±8
28	88 ±11	91 ±11	89 ±9

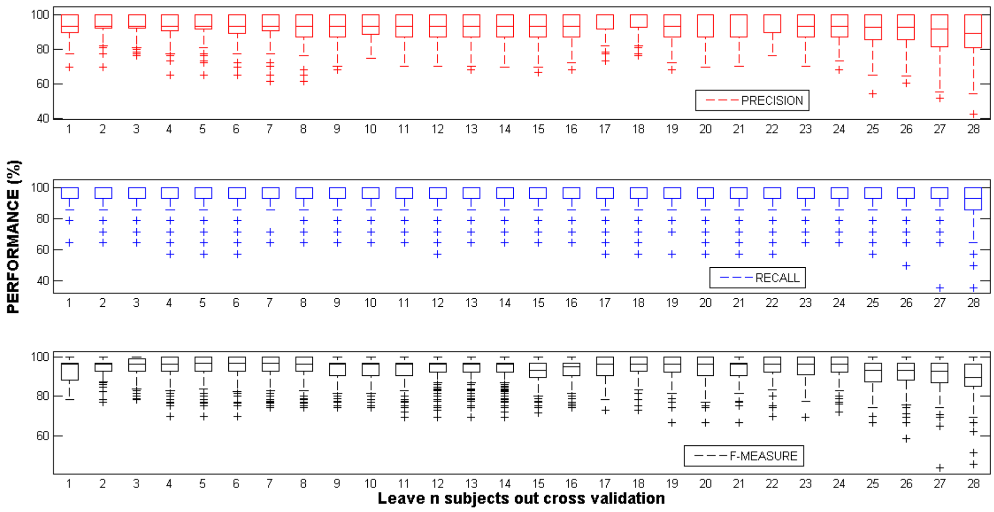

Figure 5.15: Leave n subjects out cross validation ($n = 1 : 28$)

in performance of the micro-annotation fall detection algorithm over a commercial fall detector. This section is discussed under 2 questions: 1) How does training a decision tree model with all features in a feature vector compares with the optimum set of features selected in Table 5.3? 2.) How does the micro-annotation tree based algorithm compare in terms of performance with the commercial Tynetec fall detector?

5.6.1 How does training a decision tree model with all features in a feature vector compare with an optimum set of features?

Feature extraction was discussed in Section 5.3.2, Page 59, and the 28 features extracted are shown in Table 5.2, Page 62. In order to identify and exclude features which contributed little or no information in a training set, the Wrapper method (a feature selection method) was applied to select an optimum set of features for algorithm development. Thirteen features were selected out of the 28 features in the feature vector (see Table 5.3, Page 64). This section compares the performance between the models based on all 28 features (feature vector) and the 13 selected optimum features. Maintaining performance with fewer features reduces the amount of system resources and time required for training a tree. A summary of the results is shown in Figure. 5.16. The results show that training with 13 features presented an F-M with a mean of 93.2%, an upper quartile of 96.6% and a lower quartile of 88.2% while training with all features presented an F-M with a mean of 91.2%, an upper quartile of 100% and a lower quartile of 85.6%. Overall, training with only 13 features produces similar results to training with all features. Considering that only 13 features were selected out of 28 features, training with less than half of the features in the feature vector is sufficient to train a classifier with performance over 90%, and thus reducing the amount of computation required to implement the algorithm.

5.6.2 How does a micro-annotation tree bases algorithm compare in terms of performance with a commercial based Tynetec fall detector?

This section compares the performance between a commercial fall detector (Tynetec fall detector) and the micro-annotation based machine learning fall detection algorithm developed in this thesis. A summary of the comparison is shown in Table 5.7.

Two different comparisons was performed:

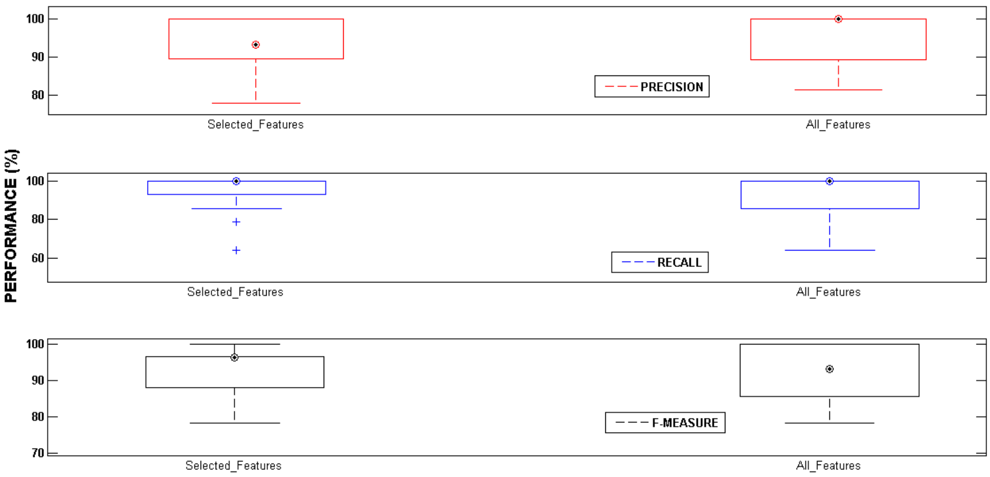

Figure 5.16: Comparison between training with selected features and all features

Table 5.6: A summary of results for training with 13 selected features and all features in a feature vector

	Selected features (13)			All features (28)		
	PR (%)	RC (%)	F-M (%)	PR (%)	RC (%)	F-M (%)
Mean	93.5	94.0	93.2	94.2	90.4	91.2
Median	93.3	100	96.6	100	100	93.3
Upper quartile	100	100	96.6	100	100	100
Lower quartile	89.6	92.9	88.2	89.2	85.7	85.6
Max	100	100	100	100	100	100
Min	70.0	64.3	78.3	68.4	28.6	44.4

Table 5.7: Comparison between micro-annotation based algorithm and a commercial based fall detector

Fall detection system	PR (%)	RC (%)	F-M (%)
Micro-annotation	96 ±6	94 ±15	94 ±12
Commercial fall detector	81 ±14	36 ±15	50 ±15

- **C 1**: Compares the performance during a protocol that consists of falls and ADL described in Section 3.1.4, Page 32.
- **C 2**: Compares the performs during ascending and descending a staircase as described in Section 3.1.5, Page 33.

C 1: This section compares the performance of a Tynetec fall detector against the micro-annotation fall detection algorithm. Dataset 4 from 22 subjects from Protocol 4 (see Table 3.1, Page 26) during a series of scripted ADL and falls was used during this exercise. This comparison aims to determine how both the micro-annotation fall detection algorithm and the Tynetec fall detector compare when exposed to similar falls and ADL for normal daily use. From the results, micro-annotation algorithm provides an F-M of 92% (sampling at 10 Hz), while the Tynetec fall detector had an F-M of 50%. From the results, the micro-annotation fall detection algorithm provides an improvement of over 40% F-M over the Tynetec fall detector.
C 2: Some ADL are more challenging to perform than others, and may result in sudden movement which can produce high acceleration signals similar to falls. For instance, ascending and descending a staircase generates acceleration signals with high peaks, which sometimes can be similar to falls. In addition, ascending and descending a staircase is an example of ADL that is frequently performed by elderly people. The protocol designed for this comparison were described in Section 3.1.5, Page 33. Thus, this evaluation investigates whether ADL such as ascending and descending a staircase will trigger false alarms in the Tynetec fall detector and the micro-annotation based fall detection algorithm. A leave one subject out cross validation was performed by 42 subjects (a combination of subjects from Protocol 2 and Protocol 3). Results showed no false alarm was triggered by the micro-annotation based algorithm, while 2 false alarms were triggered by the Tynetec detector. As noted in Section 3.1, Page 25, internal data from the Tynetec fall detector is not accessible. Instead, a trigger button on the fall detector was activated to determine how many falls were correctly classified. From the results, the micro-annotation fall detection algorithm is less likely to trigger false alarm compared to the Tynetec fall detector when subjects are ascending and descending a staircase.

5.7 Summary

The work in this chapter presents the micro-annotation fall detection algorithm and defines a design space for a tree based fall detection algorithm. The features computed for the micro-annotation fall detection algorithm is based on 3 stages of fall (pre-impact, impact and post-impact). By developing features based on these fall stages, features unique to falls are included in the decision tree. This implies that the micro-annotation based algorithm can detect falls that have these 3 stages for different fall types even if the fall types are not included in the training set. In addition, the algorithm was implemented such that it can be evaluated at a micro-level (that is, each output sample of a classifier can be compared against its corresponding sample annotation). An evaluation of the micro-annotation algorithm demonstrated a higher performance than the current state of the art (F-M $>$ 90%).

For the definition of a design space, 4 factors that impact on performance were investigated. The factors investigated are: optimum feature subset, sensor placement, minimum sampling rate and training size. A feature selection algorithm (Wrapper feature selection method) was used in WEKA to select a subset of features that provides optimum performance.Thirteen features in Table 5.3 were thus selected to provide an optimum performance out the 28 features in the feature vector.

Sensor placement was investigated and the performance between algorithms developed for sensors placed on the chest and thigh was compared. From the results, placing the sensor on the chest provides a higher performance than on the thigh. This result is in line with those identified in the literature [30, 36] that states that chest is the best location to place fall detection sensor nodes.

The analysis to determine the minimum sampling frequency required to train a tree based algorithm found that sampling at 10 Hz was sufficient for training a decision tree with an F-M of 93%. Sampling at higher frequencies will require more hardware resources and reduce the battery life.

Based on the evaluation for determining the minimum number of subjects required for training, it was found that training with between 6 and 10 subjects is sufficient for the tree based fall detection algorithm. Training with more than 12 subjects does not significantly improve performance.

Chapter 6

Conclusions and Future Work

The work in this thesis focused on two key aspects of fall detection systems:

1. The development of accurate algorithms for automatic detection of falls.
2. The definition of a design space and identification of optimal parameters for machine learning based fall detection algorithms of the type proposed.

To support the investigation, data gathering protocols for the simulation of falls and Activities of Daily Livings (ADLs) were designed. Chapter 3 presented a detailed description of the data gathering protocols used in this thesis. The protocols were designed to simulate real-life falls as much as possible within the constraints of a laboratory environment.

Overall, four fall detection algorithms were developed and evaluated (discussed in Chapters 4 and 5). Three metrics (Precision (PR), Recall (RC) and F-Measure (F-M)) were used in the evaluation of the algorithms developed, with F-measure being the focus. Precision provides information on how False Positives (FPs) impact the detection performance, recall indicates how False Negatives (FNs) impact the detection performance, and F-M combines both precision and recall to provide a single performance metric. In Chapter 4, three fall detection algorithms were evaluated. The best performing of these was a C4.5 decision tree based algorithm using as input 3D acceleration and angular velocity, along with Vector Magnitude (VM) calculated for each. This algorithm provided an F-measure of 86.4%. The remaining algorithms (logistic regression and dot-product) provided F-measures of 82.3% and 69.7%, respectively.

Based on the performance of the decision tree based algorithm combined with a survey of existing work in the literature, it was determined that machine learning algorithms of this type provide a promising solution for fall detection. Therefore, the decision tree based algorithm was extended (in Chapter 5) via the use of a new annotation technique named micro-annotation and the consideration of three distinct fall stages. The evaluation of this algorithm demonstrated an F-M of 94%.

Finally, an assessment of the design space for the micro-annotation based algorithm was performed and the optimal parameters to provide accurate fall detection were determined.

The following sections answer the research questions posed in Chapter 1 (Section 6.1) and propose future work (Section 6.2).

6.1 Research questions

The research questions that guided the work in this thesis are:

1. Can machine learning based fall detection algorithms provide performance beyond the current state of the art?
2. Compared to the use of a large set of data features, can a subset be selected that does not compromise detection accuracy?
3. What is the design space for a machine learning based fall detection algorithm?

Answers to these research questions are presented in the subsections that follow.

6.1.1 Can machine learning based fall detection algorithms provide performance beyond the current state of the art?

Yes, the performance of a fall detection algorithm can be improved beyond the current state of the art. Bagala *et al.* [8] evaluated 13 algorithms and found them to have F-measures below 90%. This conclusion was supported by implementation and evaluation of existing algorithms by the author here. The baseline performance considered here is therefore an F-measure of 90%. An evaluation of the micro-annotation based fall detection algorithm in Chapter 5 using leave one subject out cross-validation for 32 subjects provided an F-measure of 93% for sampling at 10 Hz and 94% for sampling at 25 Hz. Placing the sensor at the chest region and sampling at 25 Hz provided the best results.

6.1.2 Compared to the use of a large set of data features, can a subset be selected that does not compromise detection accuracy?

A wrapper feature selection algorithm was used for feature selection, which selected 13 features out of 28 original features considered. The features were extracted based on the 3 main fall stages (pre-impact, impact and post-impact) identified in Chapter 5. A different combination of features were selected for each fall stage. The selected features for each stage are:

- Pre-impact stage: Variance, Signal Magnitude Area (SMA), Exponential Moving Average (EMA), min of VM, and Energy
- Impact stage: Variance, Root Mean Square (RMS), EMA, State of activity, Energy, and max of VM
- Post-impact stage: Variance and forward-backward tilt angle

An evaluation comparing the performance between trees based on all 28 features and trees based on only a selected 13 features showed that there is no significant impact on detection accuracy.

6.1.3 What is the design space for a machine learning based fall detection algorithm?

The design space for machine learning based fall detection algorithms was investigated and optimal parameters found for the algorithm presented here. These are as follows:

- Extracted data features: Thirteen features as presented in Section 6.1.2, with three groups corresponding to the three stages of a fall.
- Number of sensors: 1 with 3D accelerometer and gyroscope.
- Sensor location: Chest.
- Sampling frequency: 10 Hz (though sampling at 25 Hz increased F-measure result by 1%).
- Minimum number of subjects for training: 10.

6.2 Future work

There are several areas of future work that can be investigated to expand on the work presented in this thesis. This section presents such areas that serve to improve the system functionality and provide additional evaluation of its performance.

Evaluate the fall detection algorithm on the elderly and disabled

The elderly and infirm people are the primary end-users of fall detection solutions. However, due to ethical concerns, the algorithms developed in this thesis were only evaluated using data from young and healthy subjects. Thus, it is necessary that the proposed micro-annotation based machine learning algorithm is evaluated on data gathered from the elderly and disabled subjects.

Evaluate the micro-annotation fall detection algorithm in a real-life scenario

This thesis focused on the off-line evaluation of the micro-annotation fall detection algorithm and thus specified some guidelines for algorithm development in Section 5.5, Page 63. The guidelines specified can be further investigated and their impact on algorithm and overall system performance in a real-life, real-time scenario can be determined. For instance, a minimum sampling frequency of 10 Hz was established in the thesis. The impact of this sampling frequency on battery life can be investigated.

Define guidelines for fall detection algorithm

Some of the factors that can impact on the performance of a micro-annotation based algorithm were investigated in Section 5.5, Page 63. This investigation allowed for guidelines necessary for algorithm development to be specified. The guidelines for micro-annotation based algorithm have not been fully investigated. Thus further analysis is necessary to provide detailed guidelines for the fall detection algorithm.

Investigate near-fall detection

A review of the literature conducted in Section 2.1.3, Page 7, showed that near-falls occur more often than falls and multiple near-falls can be an indication that an individual is likely to experience a fall in the future. In protocol 2 (see Section 3.1.4, Page 32), during data gathering, near-fall data were also collected and used in fall detection algorithm development. However, the micro-annotation based algorithm has not been fully developed to allow for the detection of near-falls with high accuracy. Therefore, this leaves scope for further research in extending the micro-annotation algorithm for near-falls detection.

6.3 Summary

This thesis has demonstrated that fall detection can be improved beyond the current state of the art. The micro-annotation based machine learning algorithm proposed in this thesis provides a promising solution for fall detection. The micro-annotation based algorithm generalises well for different fall types as its features are computed based on the fall stages identified in Section 2.1.2. An F-measure above 90% was achieved for evaluation based on leave one subject out cross validation.

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Appendix A

Hardware Platform and Sensors

The hardware platform used worn by subjects during data acquisition is the SHIMMER, an acronym for Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability. Fig A.1 shows SHIMMER board and integrated devices.

Two SHIMMER sensor nodes strapped to the chest and thigh of subjects were used for data acquisition and transmission from subjects to a remote PC. Each sensor node consists of a 3D accelerometer and 3D gyroscope, a Bluetooth device and an MSP430F1611 microcontroller device. The SHIMMER sensor node is shown in Fig. 3.2, weighs 27g and has a dimension of (53 x 32 x 19) mm.

The tri-axial gyroscope consists of an InvenSense IDG-500 dual-axis (X, and Y) and ISZ-500 single axis (Z) angular rate sensor MEMS from Freescale Semiconductor, with a full scale range ±8.7 rad.s^{-1}, and a sensitivity of 110 mV.rad^{-1}.s. The tri-axial accelerometer (MMA7260Q) from Freescale Semiconductor has a range up to $\pm 6g$. The Bluetooth device (Rovering Network RN-42) has a range exceeding 10 m, a default transmission rate of 115 kbaud, and is a class 2 Bluetooth module.

A.1 Sensors unit conversion

Accelerometer unit conversion To convert accelerometer data from raw values to g, a conversion formula provided in SHIMMER application note was used. The values derived for the midpoints and sensitivity are shown in table A.1 The SHIMMER sensor was place on a flat surface on each axis oriented to observe +1g and -1g acceleration. The data was sampled at 100 Hz and averaged over 5s to derive static reading for each axis.

$$A_n(g) = \frac{S_n * (A_n - M_n)}{372} \tag{A.1}$$

A_n−Accelerometer raw value for each axis

M_n−Calculated midpoint for each axis. The midpoint is the average sensor reading between the positive +g and -g

S_n−Sensitivity correction constant for each axis provided in the application note

$A_n(g)$−Acceleration in g ($10ms^{-2} = 1g$)

Table A.1: Acceleration unit conversion

Chest sensor node				Thigh sensor node			
Axis	X	Y	Z	Axis	X	Y	Z
M_n	1900.5	1956	1952.5	M_n	1938	1920	1950
S_n	1.139	1.075	1.099	S_n	0.979	1.110	1.124

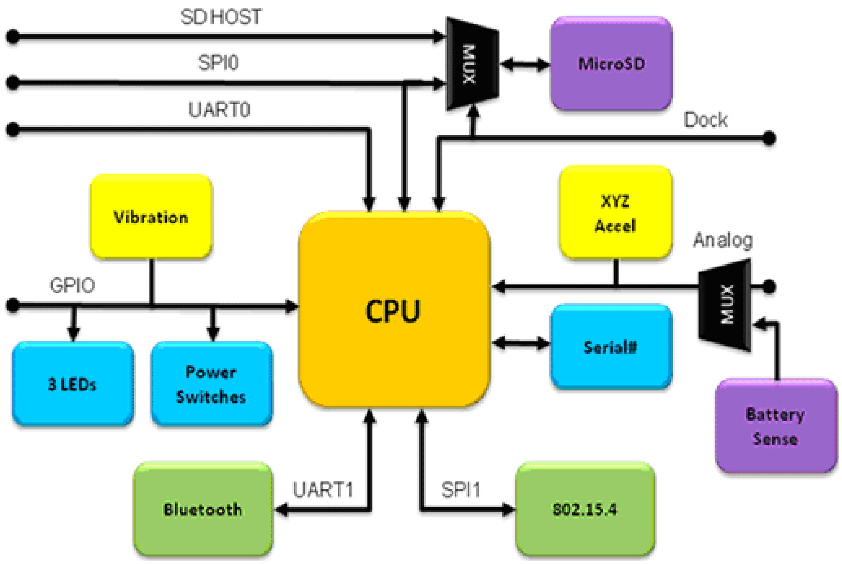


Figure A.1: SHIMMER board and integrated devices

Table A.2: Gyroscope unit conversion: static output

Chest			Thigh		
X	Y	Z	X	Y	Z
1822	1818	1950	1828	1829	1855

372−ideal sensitivity provided in the application note

Gyroscope unit conversion For the gyroscope unit conversion, each SHIMMER sensor node was place on a flat surface and data sampled at 100 Hz was averaged over 5s. The conversion from raw data to deg/s is the difference between sensor data while sensor is in motion and when sensor is static, divided by the sensitivity. Typical gyroscope static reading used in this thesis is shown in figure A.2.

$$G_n = \frac{(G_{adc} - G_{n0})}{2.731} \tag{A.2}$$

G_n−Gyroscope scaled output in deg/s

G_{adc}−Gyroscope raw value for each axis

G_{n0}−Gyroscope static output

2.731−ideal sensitivity

Data pre-processing A custom program written in Labview was used in acquiring data via Bluetooth from each SHIMMER node. The acquired data was then scaled as described in Section A.1 and re-sampled at 10Hz. Once data has been scaled, re-sampled and suitable for training a classifier, it was converted into a ARFF data format. A ARFF data format is a format required by Waikato Environment for Knowledge Analysis (WEKA), for machine learning algorithm development.

Appendix B

Ethical Approval Forms

Medium to High Risk Research Ethics Approval
Read this first

Who should use this checklist?

You should only use this checklist if you are carrying out research or consultancy project through Coventry University: This includes:

- Members of academic, research or consultancy staff.
- Honorary and external members of staff.
- Research degree students (MA/MSc by Research, MPhil or PhD).
- Professional degree students (EdD, EngD, DClinPsyc, DBA etc).
- Undergraduate students who have been directed to complete this checklist.
- Taught postgraduate students who have been directed to complete this checklist.

Who should not use this checklist?

You should not use this checklist if you are:

- An undergraduate student (Use the low risk ethics approval checklist first).
- A taught postgraduate student (Use the low risk ethics approval checklist first).
- A member of staff evaluating service level quality (Use the low risk ethic approval checklist first)
- Carrying out medical research or consultancy involving the NHS (Use the NHS online Research Ethics Committee approval form).

Can I begin work before the project is ethically approved?

No. Primary data collection can not begin until you have approval from one of the following:

- The University Applied Research Committee (UARC)
- The Research Degrees Sub-Committee (RDSC)
- An External Research Ethics Committee (NHS Research Ethics Committee, Lead Partner University etc)

Alternatively, if you have established that your project does not require ethical approval using:

- Low Risk Ethical Approval Checklist
- Medium to High Risk Research Ethics Approval Checklist

What will happen if I proceed without approval or falsely self-certify research ethics approval?

Collecting primary data in the absence of ethical approval or falsely self-certifying the level of risk associated with a project will constitute a **disciplinary offence**.

- For **Students –** this means disciplinary action resulting in immediate failure in any module or project associated with the research and potentially dismissal from the University.
- For **Staff –** This means disciplinary action, which may potentially lead to dismissal.

If you do not have ethical approval, the University's insurers will not cover you for legal action or claims for injury. In addition, you may be debarred from membership of some professional or statutory bodies and excluded from applying for some types of employment or research funding opportunities.

What happens if the project changes after approval?

If after receiving ethical approval your project changes such that the information provided in this checklist is no longer accurate, then the ethical approval is automatically suspended.

You must re-apply for ethical approval immediately and stop research based on the suspended ethical approval.

What about multi-stage projects?

If you are working on a project which involves multi-stage research, such as a focus group that informs the design of a questionnaire, you need to describe the process and focus on what you know and the most risky elements. If the focus group radically changes the method you are using then you need to re-apply for the ethical approval.

Is there any help available to complete this checklist?

Guidance can be found in the ethics section of the Registry Research Unit Intranet. You will find documents dealing with specific issues in research ethics and examples of participant information leaflets and informed consent forms. Further advice is also available from:

- Director of Studies (Students)
- Faculty Research Ethics Leader (Academic Staff)
- Registry Research Unit (Students and Staff)

Which sections of the checklist should I complete?

<table>
<tr><th>If your project involves:</th><th>Please complete sections</th></tr>
<tr><td>Desk-research only, using only secondary or published sources.</td><td>1, 2 and 16</td></tr>
<tr><td>An application to an External Research Ethics Committee other than the NHS.</td><td>1 to 4 and 16</td></tr>
<tr><td>Collection and/or analysis of primary, unpublished data from, or about, identifiable, living humans (either in laboratory or in non-laboratory settings).</td><td rowspan="4">1 to 15 and 16</td></tr>
<tr><td>Collection and/or analysis of data about the behaviour of humans in situations where they might reasonably expect their behaviour not to be observed or recorded.</td></tr>
<tr><td>Collection and/or analysis of primary, unpublished data from, or about, people who have recently died.</td></tr>
<tr><td>Collection and/or analysis of primary, unpublished data from, or about, existing agencies or organisations.</td></tr>
<tr><td>Investigation of wildlife in its natural habitat.</td><td>1 to 5, 15 and 16</td></tr>
<tr><td>Research with animals other than in their natural settings.</td><td rowspan="2">Do not complete this checklist. Contact the Registry Research Unit for advice</td></tr>
<tr><td>Research with human tissues or body fluids.</td></tr>
<tr><td>Research involving access to NHS patients, staff, facilities or research which requires access to participants who are mentally incapacitated.</td><td>Do not complete this checklist. Make an application using the on-line NHS Research Ethics Committee approval form</td></tr>
</table>

How much details do I need to give in the checklist?

Please keep the details as brief as possible but you need to provide sufficient information for peer reviewers from the Research Ethics Panel to review the ethical aspects of your project.

Who are the Faculty Research Ethics Leaders?

Check the Registry Research Unit Intranet site for the most up to date list of Faculty Research Ethics Leaders.

How long will it take to carry out the review?

If your project requires **ethical peer review** you should submit this to the Registry Research Unit at **least three** months before the proposed start date of your project.

How do I submit this checklist?

The completed checklist and any attachments must be submitted to ethics.uni@coventry.ac.uk

Medium to High Risk Research Ethics Approval Checklist

1 Project Information (Everyone)

Title of Project Wireless Instrumentation for fall detection
Name of Principal Investigator (PI) or Research or Professional Degree Student Olukunle Ojetola
Faculty, Department or Institute Engineering and Computing
Names of Co-investigators (CIs) and their organisational affiliation
How many additional research staff will be employed on the project? Names and their organisational affiliation (if known)
Proposed project start date (At least three months in the future) June 2010
Estimated project end date 2012
Who is funding the project? Mr Ojetola Has funding been confirmed? Yes
Code of ethical practice and conduct most relevant to your project: • British Computer Society

Students Only

Degree being studied (MSc/MA by Research, MPhil, PhD, EngD, etc) PhD
Name of your Director of Studies Prof. Elena Gaura
Date of Enrolment 27th September, 2009

2. Does this project need ethical approval?

Questions	Yes	No
Does the project involve collecting primary data from, or about, living human beings?	X	
Does the project involve analysing primary or unpublished data from, or about, living human beings?	X	
Does the project involve collecting or analysing primary or unpublished data about people who have recently died other than data that are already in the public domain?		X
Does the project involve collecting or analysing primary or unpublished data about or from organisations or agencies of any kind other than data that are already in the public domain?		X
Does the project involve research with non-human vertebrates in their natural settings or behavioural work involving invertebrate species not covered by the Animals Scientific Procedures Act (1986)?[1]		X
Does the project place the participants or the researchers in a dangerous environment, risk of physical harm, psychological or emotional distress?	X	
Does the nature of the project place the participant or researchers in a situation where they are at risk of investigation by the police or security services?		X

If you answered **Yes** to **any** of these questions, proceed to **Section 3**.

If you answered **No** to **all** these questions:

- You **do not** need to submit your project for peer ethical review and ethical approval.
- You should sign the Declaration in **Section 16** and keep a copy for your own records.
- Students must ask their Director of Studies to countersign the declaration and they should send a copy for your file to the Registry Research Unit.

[1] The Animals Scientific Procedures Act (1986) was amended in 1993. As a result the common octopus (*Octopus vulgaris*), as an invertebrate species, is now covered by the act.

3 Does the project require Criminal Records Bureau checks?

Questions	Yes	No
Does the project involve direct contact by any member of the research team with children or young people under 18 years of age?		X
Does the project involve direct contact by any member of the research team with adults who have learning difficulties?		X
Does the project involve direct contact by any member of the research team with adults who are infirm or physically disabled?		X
Does the project involve direct contact by any member of the research team with adults who are resident in social care or medical establishments?		X
Does the project involve direct contact by any member of the research team with adults in the custody of the criminal justice system?		X
Has a Criminal Records Bureau (CRB) check been stipulated as a condition of access to any source of data required for the project?		X

If you answered **Yes** to **any** of these questions, please:

- Explain the nature of the contact required and the circumstances in which contact will be made during the project.

4 Is this project liable to scrutiny by external ethical review arrangements?

Questions	Yes	No
Has a favourable ethical opinion been given for this project by an external research ethics committee (e.g. social care, NHS or another University)?		X
Will this project be submitted for ethical approval to an external research ethics committee (e.g. social care, NHS or another University)?		X

If you answered **No** to **both** of these questions, please proceed to **Section 5**.

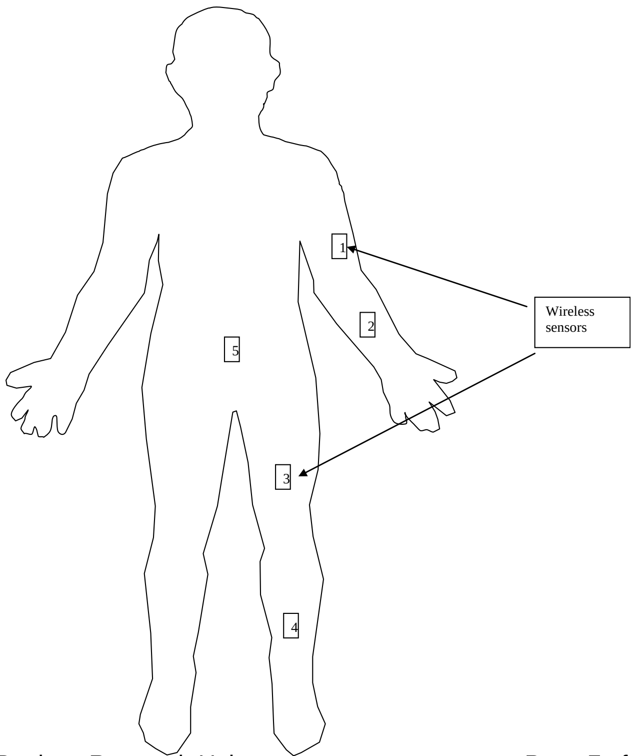
If you answered **Yes** to **either** of these questions:

- Sign the Declaration in **Section 16** and send a copy to the Registry Research Unit.
- Students must get their Director of Studies to countersign the checklist before submitting it.

5 More detail about the project

What are the aims and objectives of the project? The aim is to design a system that uses wireless sensors for fall detection. It is expected that the data gathered will provide further information on how the body tries to compensate for loss of balance before a fall occurs.
Briefly describe the principal methods, the sources of data or evidence to be used and the number and type of research participants who will be recruited to the project. Each participant will be asked to stand on a balance board with five wireless sensors strapped to their limbs and waist. Two wireless sensors will be strapped to one arm; two other wireless sensors will be strapped to one leg, and one wireless sensor will be strapped to the waist. The research participants will mainly be friends and colleagues (between 10 and 20 participants)
What research instrument(s), validated scales or methods will be used to collect data? Sensors (Accelerometers and gyroscopes), and microcontrollers
If you are using an externally validated research instrument, technique or research method, please specify. I am not using an externally validated research instrument.
If you are not using an externally validated scale or research method, please attach a copy of the research instrument you will use to collect data. For example, a measurement scale, questionnaire, interview schedule, observation protocol for ethnographic work or, in the case of unstructured data collection, a topic list.

Wireless sensor boards consisting of accelerometers, gyroscope, microcontroller (MSP430), and ZigBee transceiver will be strapped to the waist and limbs of each participant. Each participant will be asked to stand on a balance board, balancing as best as he or she could. Five wireless sensors will be strapped to the participant's waist and limbs with the aim to acquire acceleration data and orientation of the participant's body. The aim is to record how the limbs move while trying to maintain balance and how the body compensates when there is loss in balance. The session will take 15 minutes.



6 Confidentiality, security and retention of research data

Questions	Yes	No
Are there any reasons why you cannot guarantee the full security and confidentiality of any personal or confidential data collected for the project?		X
Is there a significant possibility that any of your participants, or people associated with them, could be directly or indirectly identified in the outputs from this project?		X
Is there a significant possibility that confidential information could be traced back to a specific organisation or agency as a result of the way you write up the results of the project?		X
Will any members of the project team retain any personal or confidential data at the end of the project, other than in fully anonymised form?		X
Will you or any member of the team intend to make use of any confidential information, knowledge, trade secrets obtained for any other purpose than this research project?		X

If you answered **No** to **all** of these questions:

- Explain how you will ensure the confidentiality and security of your research data, both during and after the project.

The participation of volunteers will be kept confidential, and only my supervisor(s) and I will have access to the raw data. All the consent forms will be stored in a separate, secure (locked) location from the raw data itself. The results of the research will be presented in a format that does not reveal the identity of the volunteers.

If you answered **Yes** to **any** of these questions:

- Explain the reasons why it is essential to breach normal research protocol regarding confidentiality, security and retention of research data.

7 Informed consent

Questions	**Yes**	**No**
Will all participants be fully informed why the project is being conducted and what their participation will involve and will this information be given before the project begins?	X	
Will every participant be asked to give written consent to participating in the project before it begins?	X	
Will all participants be fully informed about what data will be collected and what will be done with these data during and after the project?	X	
Will explicit consent be sought for audio, video or photographic recording of participants?	X	
Will every participant understand what rights they have not to take part, and/or to withdraw themselves and their data from the project if they do take part?	X	
Will every participant understand that they do not need to give you reasons for deciding not to take part or to withdraw themselves and their data from the project and that there will be no repercussions as a result?	X	
If the project involves deceiving or covert observation of participants, will you debrief them at the earliest possible opportunity?	X	

If you answered **Yes** to **all** these questions:

- Explain briefly how you will implement the informed consent scheme described in your answers.
- Attach copies of your participant information leaflet, informed consent form and participant debriefing leaflet (if required) as evidence of your plans.

Every volunteer will be given a consent form to read and sign before participating in the experiment, and a detailed explanation about the experiment will also be verbally given.

If you answered **No** to **any** of these questions:

- Explain why it is essential for the project to be conducted in a way that will not allow all participants the opportunity to exercise fully-informed consent.
- Explain how you propose to address the ethical issues arising from the absence of transparency.
- Attach copies of your participant information sheet and consent form as evidence of your plans.

8 Risk of harm

Questions	Yes	No
Is there any significant risk that your project may lead to physical harm to participants or researchers?	X	
Is there any significant risk that your project may lead to psychological or emotional distress to participants or researchers?		X
Is there any significant risk that your project may place the participants or the researchers in potentially dangerous situations or environments?		X
Is there any significant risk that your project may result in harm to the reputation of participants, researchers, their employers, or other persons or organisations?		X

If you answered **Yes** to **any** of these questions:

- Explain the nature of the risks involved and why it is necessary for the participants or researchers to be exposed to such risks.
- Explain how you propose to assess, manage and mitigate any risks to participants or researchers.
- Explain the arrangements by which you will ensure that participants understand and consent to these risks.
- Explain the arrangements you will make to refer participants or researchers to sources of help if they are seriously distressed or harmed as a result of taking part in the project.
- Explain the arrangements for recording and reporting any adverse consequences of the research.

A real fall may occur while participants stand on the balance board. It is necessary to expose participants to such risk because this research is aimed at investigating how the body compensates for loss of balance before a fall actually occurs. To cushion the effect of the fall, a duvet will be placed on the floor around the balance board, and the experiment will be performed in a clear space. In addition, elbow and knee padding will be worn by participants during the experiments. I will be standing around and be on guard should a real fall occur. Participants will be informed both verbally and on the consent form about the possible risks before they participate.

If any participant is seriously distressed or harmed as a result of the experiment, my director of studies will be informed immediately. In addition, first aiders in Armstrong Siddleley will be immediately contacted.

9 Risk of disclosure of harm or potential harm

Questions	Yes	No
Is there a significant risk that the project will lead participants to disclose evidence of previous criminal offences or their intention to commit criminal offences?		X
Is there a significant risk that the project will lead participants to disclose evidence that children or vulnerable adults have or are being harmed or are at risk of harm?		X
Is there a significant risk that the project will lead participants to disclose evidence of serious risk of other types of harm?		X

If you answered **Yes** to **any** of these questions:

- Explain why it is necessary to take the risks of potential or actual disclosure.
- Explain what actions you would take if such disclosures were to occur.
- Explain what advice you will take and from whom before taking these actions.
- Explain what information you will give participants about the possible consequences of disclosing information about criminal or serious risk of harm.

10 Payment of participants

Questions	Yes	No
Do you intend to offer participants cash payments or any other kind of inducements or compensation for taking part in your project?		X
Is there any significant possibility that such inducements will cause participants to consent to risks that they might not otherwise find acceptable?		X
Is there any significant possibility that the prospect of payment or other rewards will systematically skew the data provided by participants in any way?		X
Will you inform participants that accepting compensation or inducements does not negate their right to withdraw from the project?		X

If you answered **Yes** to **any** of these questions:

- Explain the nature of the inducements or the amount of the payments that will be offered.
- Explain the reasons why it is necessary to offer payments.
- Explain why you consider it is ethically and methodologically acceptable to offer payments.

11 Capacity to give informed consent

Questions	Yes	No
Do you propose to recruit any participants who are under 18 years of age?		X
Do you propose to recruit any participants who have learning difficulties?		X
Do you propose to recruit any participants with communication difficulties including difficulties arising from limited facility with the English language?		X
Do you propose to recruit any participants who are very elderly or infirm?		X
Do you propose to recruit any participants with mental health problems or other medical problems that may impair their cognitive abilities?		X
Do you propose to recruit any participants who may not be able to understand fully the nature of the research and the implications for them of participating in it?		X

If you answered **Yes** to **only the last two** questions, proceed to **Section 16** and then apply using the online NHS Research Ethics Committee approval form.

If you answered **Yes** to **any** of the **first four** questions:

- Explain how you will ensure that the interests and wishes of participants are understood and taken in to account.
- Explain how in the case of children the wishes of their parents or guardians are understood and taken into account.

12 Is participation genuinely voluntary?

Questions	Yes	No
Are you proposing to recruit participants who are employees or students of Coventry University or of organisation(s) that are formal collaborators in the project?	X	
Are you proposing to recruit participants who are employees recruited through other business, voluntary or public sector organisations?		X
Are you proposing to recruit participants who are pupils or students recruited through educational institutions?		X
Are you proposing to recruit participants who are clients recruited through voluntary or public services?		X
Are you proposing to recruit participants who are living in residential communities or institutions?		X
Are you proposing to recruit participants who are in-patients in a hospital or other medical establishment?		X
Are you proposing to recruit participants who are recruited by virtue of their employment in the police or armed services?		X
Are you proposing to recruit participants who are being detained or sanctioned in the criminal justice system?		X
Are you proposing to recruit participants who may not feel empowered to refuse to participate in the research?		X

If you answered **Yes** to **any** of these questions:

- Explain how your participants will be recruited.
- Explain what steps you will take to ensure that participation in this project is genuinely voluntary.

Participation is entirely voluntary. Volunteers have the right to withdraw from the study within two week after the experiments has been performed. Volunteers can withdraw by contacting me by email or telephone (provided in the consent form). If a volunteer decides to withdraw from participating, all the sensor data acquired during his experiment will be deleted and will not be used in the study. There are no consequences if a volunteer no longer wishes to participate in the study. Participants will be politely asked if they are willing to take part in the experiments.

13 On-line and Internet Research

Questions	**Yes**	**No**
Will any part of your project involve collecting data by means of electronic media such as the Internet or e-mail?		X
Is there a significant possibility that the project will encourage children under 18 to access inappropriate websites or correspond with people who pose risk of harm?		X
Is there a significant possibility that the project will cause participants to become distressed or harmed in ways that may not be apparent to the researcher(s)?		X
Will the project incur risks of breaching participant confidentiality and anonymity that arise specifically from the use of electronic media?		X

If you answered **Yes** to **any** of these questions:

- Explain why you propose to use electronic media.
- Explain how you propose to address the risks associated with online/internet research.
- Ensure that your answers to the previous sections address any issues related to online research.

14 Other ethical risks

Question	**Yes**	**No**
Are there any other ethical issues or risks of harm raised by your project that have not been covered by previous questions?		X

If you answered **Yes** to **this** question:

- Explain the nature of these ethical issues and risks.
- Explain why you need to incur these ethical issues and risks.
- Explain how you propose to deal with these ethical issues and risks.

15 Research with non-human vertebrates[2]

Questions	Yes	No
Will any part of your project involve the study of animals in their natural habitat?		X
Will your project involve the recording of behaviour of animals in a non-natural setting that is outside the control of the researcher?		X
Will your field work involve any direct intervention other than recording the behaviour of the animals available for observation?		X
Is the species you plan to research endangered, locally rare or part of a sensitive ecosystem protected by legislation?		X
Is there any significant possibility that the welfare of the target species or those sharing the local environment/habitat will be detrimentally affected?		X
Is there any significant possibility that the habitat of the animals will be damaged by the project such that their health and survival will be endangered?		X
Will project work involve intervention work in a non-natural setting in relation to invertebrate species other than *Octopus vulgaris*?		X

If you answered **Yes** to **any** of these questions:

- Explain the reasons for conducting the project in the way you propose and the academic benefits that will flow from it.
- Explain the nature of the risks to the animals and their habitat.
- Explain how you propose to assess, manage and mitigate these risks.

[2] The Animals Scientific Procedures Act (1986) was amended in 1993. As a result the common octopus (*Octopus vulgaris*), as an invertebrate species, is now covered by the act.

16 Principal Investigator Certification

Please ensure that you:

- Tick all the boxes below that are relevant to your project and sign this checklist.
- Students must get their Director of Studies to countersign this declaration.

I believe that this project **does not require research ethics peer review**. I have completed Sections 1-2 and kept a copy for my own records. I realise I may be asked to provide a copy of this checklist at any time.	
I request that this project is **exempt from internal research ethics peer review** because it will be, or has been, reviewed by an external research ethics committee. I have completed Sections 1-4 and have attached/will attach a copy of the favourable ethical review issued by the external research ethics committee. Please give the name of the external research ethics committee here: Send to ethics.uni@coventry.ac.uk	
I **request an ethics peer review** and confirm that I have answered all relevant questions in this checklist honestly. Send to ethics.uni@coventry.ac.uk	
I confirm that I will carry out the project in the ways described in this checklist. I will immediately suspend research and request new ethical approval if the project subsequently changes the information I have given in this checklist.	
I confirm that I, and all members of my research team (if any), have read and agreed to abide by the Code of Research Ethics issued by the relevant national learned society.	
I confirm that I, and all members of my research team (if any), have read and agreed to abide by the University's Research Ethics, Governance and Integrity Framework.	

Signatures

If you submit this checklist and any attachments by e-mail, you should type your name in the signature space. An email attachment sent from your University inbox will be assumed to have been signed electronically.

Principal Investigator

Signed …………..Olukunle Ojetola....................................... (Principal Investigator or Student)

Date ……13th April, 2010

Students submitting this checklist by email must append to it an email from their Director of Studies confirming that they are prepared to make the declaration above and to countersign this checklist. This email will be taken as an electronic countersignature.

Student's Director of Studies

Countersigned.. (Director of Studies)

Date ....

I have read this checklist and confirm that it covers all the ethical issues raised by this project fully and frankly. I also confirm that these issues have been discussed with the student and will continue to be reviewed in the course of supervision.

Note: This checklist is based on an ethics approval form produce by Research Office of the College of Business, Law and Social Sciences at Nottingham Trent University. Copyright is acknowledged.

For office use only

Initial assessment

Date checklist initially received:	DD/MM/YYYY	
1. Ethical review required	Yes	No
2. CRB check required	Yes	No
Submitted to an external research ethics committee		
3. External research ethics committee (Name)	Yes	No
4. Copy of external ethical clearance received	DD/MM/YYYY	
Ethics Panel Review		
5. Date sent to reviewer 1 (Name)	DD/MM/YYYY	
6. Date sent to reviewer 2 (Name)	DD/MM/YYYY	
Original Decision (Consultation with Chair UARC/Chair RDSC)		
7. Approve	Yes	No
8. Approve with conditions (specify)	Yes	No
9. Resubmission	Yes	No
10. Reject	Yes	No
11. Date of letter to applicant	DD/MM/YYYY	
Resubmission		
12. Date of receipt of resubmission:	DD/MM/YYYY	
13. Date sent to reviewer 1 (Name)	DD/MM/YYYY	
14. Date sent to reviewer 2 (Name)	DD/MM/YYYY	
Final decision recorded (Consultation with Chair UARC/Chair RDSC)		
15. Approve	Yes	No
16. Approve with conditions (specify)	Yes	No
17. Reject	Yes	No
18. Date of letter to applicant	DD/MM/YYYY	

Signature .... (Chair of UARC/Chair RDSC)

Date ....

Participant Information Sheet 1

Title of Project:
Wireless Instrumentation for fall detection

What is the purpose of the study?
The purpose is to design a system that uses wireless sensors for fall detection. As an individual is about to experience a fall either due to a slip or trip, the body tries to compensate for this loss of balance. Using acceleration and gyroscopic sensors, the movement, rotation and orientation of the body can be measured. It is expected that this data will provide further information on how the body tries to compensate for this loss of balance, and also help detect when fall actually occurs. The sensors attached to the limbs consist of an MSP430 microcontroller, a tri-axial accelerometer, and a ZigBee wireless transceiver, while the sensor attached to the waist will be similar to sensors attached to the limbs and also will include a dual axis gyroscope.

Why have I been approached?
For the purpose of this study, a number of adult participants are needed. Each participant will be asked to stand on a balance board with five wireless sensors strapped to their limbs and waist. Two wireless sensors will be strapped to one arm; two other wireless sensors will be strapped to one leg, and one wireless sensor will be strapped to the waist as shown in figure 1.

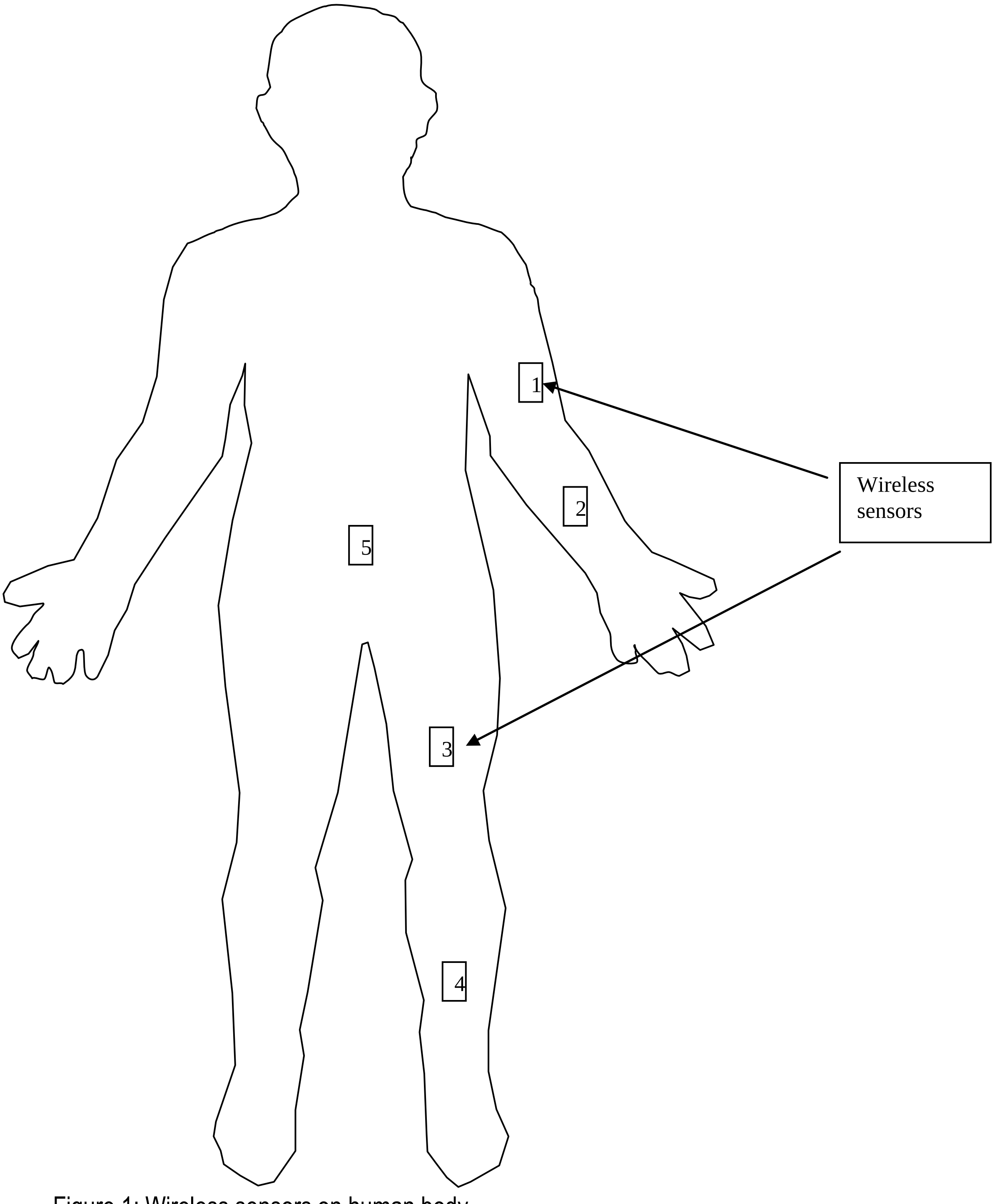


Figure 1: Wireless sensors on human body

Do I have to take part?
Participation is entirely voluntary. If you change your mind about taking part in the study you can withdraw within two week after the experiment has been performed. You can withdraw by contacting me by email or telephone (given below). If you decide to withdraw from participating, all the sensor data acquired during your experiment will be deleted and will not be used in the study. There are no consequences for deciding that you no longer wish to participate in the study.

What will happen to me if I take part?
You will be asked to stand on a balance board, balancing as best as you can. Five wireless sensors will be strapped to your waist and limbs with the aim to acquire acceleration data and orientation of your body. The aim is to record how the limbs move while trying to maintain balance and how the body compensates when there is loss in balance. The session will take 15 minutes. In these experiments, participants are not being judged by their abilities.

What are the possible disadvantages and risks of taking part?
The task may be challenging for some people while trying to gain balance and a real fall may occur. A large duvet will be placed around the balance board to cushion the effect should a real fall occur, and elbow and knee padding will be worn by participants. The experiment will be performed in a clear space.

What are the possible benefits of taking part?
The exercise may help you improve your balance and this may have positive health effects. In addition, the knowledge gained may help progress research in fall detection and wireless instrumentation.

What if something goes wrong?
If we have to cancel an experiment session I will attempt to contact you as soon as possible using the method indicated by you on the consent form.

Will my taking part in this study be kept confidential?
Your participation will be kept confidential, and only my supervisor(s) and I will have access to the raw data. All the consent forms will be stored in a separate, secure (locked) location from the raw data itself.

What will happen to the results of the research study?
The results will be written up and presented as part of my PhD thesis, and may also be presented at academic conferences and / or written up for publication in peer reviewed academic journals. The data will be presented in a way that participants will be completely anonymous.

Who is organising and funding the research?
The research is organised by Olukunle Ojetola a research student with Cogent computing Coventry University, and equipment are provided by Cogent computing.

Who has reviewed the study?
The Coventry University UARC Ethics Committee has reviewed and approved this study.

Contact for Further Information
Olukunle Ojetola

Tel: 07939618341

Email: aa4329@coventry.ac.uk

The Consent Statement

Participant Reference Code: ______________

I have read and understand the attached participant information sheet and by signing below I consent to participate in this study.

I understand that I have the right to withdraw from the study without giving a reason at any time during the study itself.

I understand that I also have the right to change my mind about participating in the study for a short period after the study has concluded (within two weeks).

Signed: ____

Print Name: ____

Witnessed by: ____

Print Name: ____

Researcher's Signature: ____

Participant Information Sheet 2

Title of Project:
Falls and Near-falls detection using wearable sensors

What is the purpose of the study?
The purpose is to design a system that uses wireless sensors for falls and near-falls detection. As an individual is about to experience a fall either due to a slip or trip, the body tries to compensate for this loss of balance. Using acceleration and gyroscopic sensors, the movement, rotation and orientation of the body can be measured. It is expected that this data will provide further information on how the body tries to compensate for this loss of balance, and also help detect when falls occur. The sensors attached to the limbs consist of an MSP430 microcontroller, a tri-axial accelerometer, tri-axial gyroscope, and a Bluetooth transceiver.

Why have I been approached?
For the purpose of this study, a number of adult participants are needed. Each participant will be requested to perform a number of Activities of Daily Living (ADL), such as standing, sitting, walking and lying. In addition, subjects will be requested to perform a number of falls (forward, backward and lateral falls). Some real-falls (forward and backward falls) will also be induced by deliberately pushing participants onto a bed with extra layers of cushion and duvet. In order to induce these real-falls, participants will be blindfolded and instructed to stand on a balance board before they are pushed onto the bed.

Further, a near-fall will be induced by instructing subjects to stand on a balance board while blindfolded and pushed gently in order to induce loss of balance.

Throughout the experiment, five wireless sensors will be strapped to participants' limbs and chest. Two wireless sensors will be strapped to one arm; two other wireless sensors will be strapped to one leg, and one wireless sensor will be strapped to the chest as shown in figure 1.

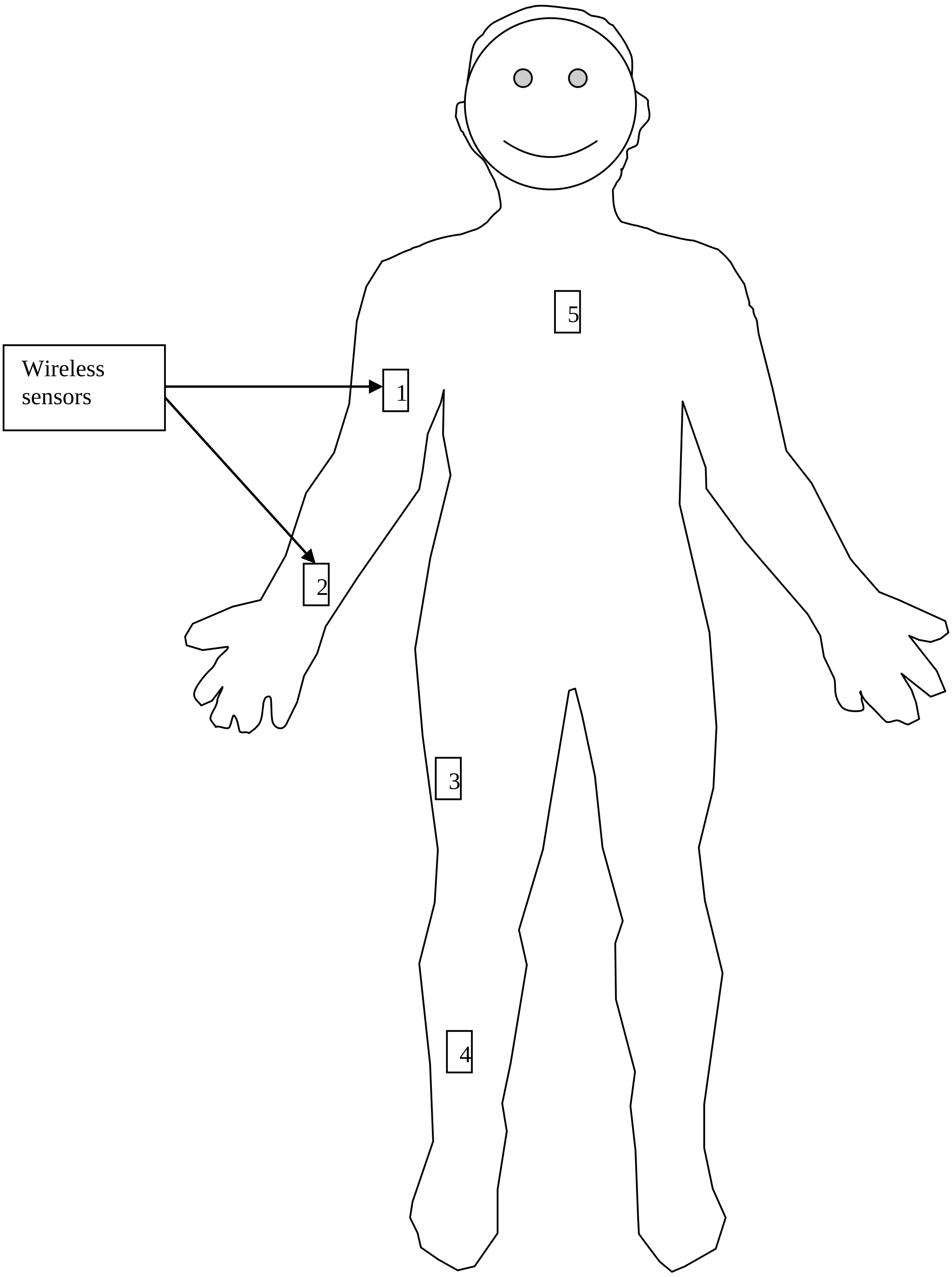


Figure 1: Wireless sensors on human body

Do I have to take part?
Participation is entirely voluntary. If you change your mind about taking part in the study you can withdraw within two week after the experiment has been performed. You can withdraw by contacting me by email or telephone (given below). If you decide to withdraw from participating, all the sensor data acquired during your experiment will be deleted and will not be used in the study. There are no consequences for deciding that you no longer wish to participate in the study.

What will happen to me if I take part?
You will be requested to perform a number of ADL, such as standing, sitting, walking and lying. In addition, you will be requested to perform a number of falls (forward, backward and lateral falls). Some real-falls (forward and backward falls) will also be induced by deliberately pushing you onto a bed with extra layers of cushion and duvet. In order to induce these real-falls, you will be blindfolded and instructed to stand on a balance board before being pushed onto the bed.

Further, a near-fall will be induce by instructing you to stand on a balance board while blindfolded and pushed gently in order to induce loss of balance.

Five wireless sensors will be strapped to your chest and limbs with the aim to acquire acceleration data and orientation of your body. The aim is to capture data during ADL, falls, record how the limbs move while trying to maintain balance and how the body compensates when there is loss in balance. The session will take about 20 minutes. In these experiments, participants are not being judged by their abilities.

What are the possible disadvantages and risks of taking part?
The task may be challenging for some people while trying to gain balance and a real fall will occur. A bed with extra layers of cushion and a large duvet will be placed around during the experiment to cushion the effect, and elbow and knee padding will be worn by participants. The experiment will be performed in a clear space.

What are the possible benefits of taking part?
The exercise may help you improve your balance and this may have positive health effects. In addition, the knowledge gained may help progress research in fall detection and wireless instrumentation.

What if something goes wrong?
If we have to cancel an experiment session I will attempt to contact you as soon as possible using the method you indicated on the consent form.

Will my taking part in this study be kept confidential?
Your participation will be kept confidential, and only my supervisor(s) and I will have access to the raw data. All the consent forms will be stored in a separate, secure (locked) location from the raw data itself.

What will happen to the results of the research study?

The results will be written up and presented as part of my PhD thesis, and may also be presented at academic conferences and / or written up for publication in peer reviewed academic journals. The data will be presented in a way that participants will be completely anonymous.

Who is organising and funding the research?
The research is organised by Olukunle Ojetola a research student with Cogent computing Coventry University, and equipment are provided by Cogent computing.

Who has reviewed the study?
The Coventry University UARC Ethics Committee has reviewed and approved this study.

Contact for Further Information
Olukunle Ojetola

Tel: 07939618341
Email: aa4329@coventry.ac.uk

The Consent Statement

Participant Reference Code: ______________

I have read and understand the attached participant information sheet and by signing below I consent to participate in this study.

I understand that I have the right to withdraw from the study without giving a reason at any time during the study itself.

I understand that I also have the right to change my mind about participating in the study for a short period after the study has concluded (within two weeks).

Signed: ____

Print Name: ____

Witnessed by: ____

Print Name: ____

Researcher's Signature: ____

Appendix C

Publications

The following select publications follow:

- **O. Ojetola**, E.I. Gaura, and J. Brusey. **Fall detection with wearable sensors - SAFE (SmArt Fall dEtection)**. In *Intelligent Environments (IE), 2011 7th International Conference on*, pages 318-321, 25-28 July 2011, Nottingham, UK.
- **O. Ojetola**, E.I. Gaura, J. Brusey, and D. Thake. **Machine learning for fall detection**. *Sensors and Interface for Cyber-Physical Systems*. N.Medrano, IGI Global Inc. (in print)
